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MASTER'S THESIS

Competition and Innovation: Revisiting the Relationship Using Alternative Measures of Rivalry

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Declaration of Authorship

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Prague, July 27, 2015

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Abstract

This study re–examines the relationship between competition and innovation in a detailed firm–level dataset of publicly traded US companies spanning from 1975 to 2013. Using R&D expenditures, patent counts and patent citations as the measures of innovation, and Herfindahl–Hirschman Index, Lerner Index, Profit Elasticity and Product Market Fluidity as the proxies for competition we document a robust positive association between the two variables, as well as strong evidence of the non–linear relationship known as “inverted–U shape”, when controlling for size, distance to technological frontier, level of knowledge spillovers, technological opportunities and other firm– and industry–specific characteristics. We address overdispersion in the data by using negative binomial and zero–inflated negative binomial count data regressions, and the results are robust in these specifications. Additionally, in order to address potential endogeneity issues, we employ a set of instruments based on the import tariff rates and the level of Chinese import penetration, and find a weak evidence of positive relationship as well. Overall the results strongly support the prediction of agency models, “replacement effect” and “escape–competition effect” about the positive influence of competition on innovation.

JEL Classification	D40, L10, L22, O31, O51
Keywords	competition, innovation, profit elasticity, product market fluidity, inverted–U, negative binomial regression

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Abstrakt

Tato studie přezkoumá vztah mezi konkurencí a inovací na základě podrobného souboru dat, představených na firemní úrovni, veřejně obchodovaných amerických společností v časovém úseku od roku 1975 do roku 2013. Používáním výdajů na výzkum a rozvoj, patentových počtů a patentových citací jako měřitko inovace, a Herfindahl–Hirschmanůvého indexu, Lernerůvého indexu, cenové elasticity a proměnlivosti trhu výrobků jako náhrady pro konkurenci, my sledujeme robustní pozitivní vztah mezi dvěma proměnnými, stejně jako silný důkaz existence nelineárního vztahu známého jako "obrácená U–křivka", při kontrole velikosti, vzdálenosti od technologické hranice, úrovně přelévání znalostí, technologických možností a dalších firemně a průmyslově specifických vlastností. Nadprůměrnou disperzi v datech řešíme použitím negativní binomické a nulou–nahuštěné negativní binomické početních datových regresí, a výsledky jsou robustní vzhledem k těmto změnám ve specifikacích. Navíc, s cílem vyřešit potenciální problémy endogenity, používáme řadu instrumentů, založených na celní sazbě z dovozu a úrovni čínského importní průniku, a stejně nacházíme slabý důkaz pozitivního vztahu. Celkový výsledek v značné míře podporuje predikci agenturní modely, "náhrazujícího efektu" a "efektu úniknutí konkurence" o pozitivním vlivu hospodářské konkurencí na inovaci.

Klasifikace JEL	D40, L10, L22, O31, O51
Klíčová slova	konkurence, inovace, pružnost zisku, proměnlivost trhu výrobků, obrácená U–křivka, negativní binomická regrese

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Acronyms

2SLS Two–Stage Least Squares

CI Citation Index

DOJ Department of Justice

DTF Distance to Technological Frontier

EPO European Patent Office

FTC Federal Trade Commission

HHI Herfindahl–Hirschman Index

IV Instrumental Variable

IO Industrial Organization

LI Lerner Index

M&A Mergers and Acquisitions

NAICS North American Industry Classification System

NB Negative Binomial

NBER National Bureau of Economic Research

OECD Organization for Economic Co-operation and Development

PCM Product Market Competition

PE Profit Elasticity

PMC Product Market Competition

PMF Product Market Fluidity

PP&E Property, Plant and Equipment

R&D Research and Development

ROI Return on Investment

RPD Relative Profit Difference

SIC Standard Industrial Classification

TFP Total Factor Productivity

TO Technological Opportunity

USPTO United States Patent and Trademark Office

WTO World Trade Organization

Master's Thesis Proposal

Author	Anton Astakhov
Supervisor	prof. M.Sc. Jiří Novák, Ph.D.
Proposed topic	Competition and Innovation: Revisiting the Relationship Using Alternative Measures of Rivalry

Topic characteristics My work will contribute to the debate between proponents of contradicting views on relationship between level of competition and incentive to innovate: those expressed in Arrow (1962) and in Schumpeter (1934). Schumpeterian proposition that perfectly competitive market cannot be considered the most efficient platform for innovation due to decreased monopoly rent was later challenged by Arrow, who argued that "the preinvention monopoly power acts as a strong disincentive to further innovation". A compromise was offered in Aghion *et al.* (2005), implying an "inverted–U shape" relationship between level of competition and innovation, where both "escape competition" and "Schumpeterian" motives are accounted for. In macro finance this debate is primarily narrowed down to antitrust regulation issues.

As noted by Gilbert (2006), empirical evidence on the issue is mixed. While Aghion *et al.* (2005), Bos *et al.* (2013), Hashmi (2013) and others were able to confirm the inverted–U hypothesis, the metrics of innovative performance and rivalry in the industry used in this and other research are methodologically problematic (Nickell 1996). This work expands on the previous research by introducing qualitatively new measures of product market competition, developed in Hoberg *et al.* (2014) and Boone (2008), known as *product market fluidity* and *profit elasticity* respectively. Innovative performance metrics are reviewed as well, improving on typically used and widely criticized variables such as R&D expenditures and raw patent counts. In addition, following Aghion *et al.* (2005) and subsequent research, the thesis will account for other exogenous variables which influence competition, such as the distance of firm to technological frontier.

Hypotheses

1. Innovative performance of a company is positively (negatively) associated with the level of rivalry in the industry.

2. Innovative performance of a company has a non–linear, inverted–U shape relation with the level of rivalry in the industry.

3. Innovative performance of a company is positively (negatively) associated with the distance to technological frontier.

Methodology The main research question of strength and shape of the relationship between competition and innovation can be tested with a simple OLS regression, expanding into piecewise regressions in order to test for non–linearity. The dependent variable can be represented by R&D or patent metrics, discussed in *e.g.* Hirschey & Richardson (2004), who provide a good summary of scientific indicators, which can be used as dependent variable, such as patent count, patent citation index, non-patent references, technology cycle time *etc.* Alternatively, a combined metric of patent's scientific merit can be developed using principal component analysis.

Independent variable, representing the degree of competition, can be proxied by such metrics as firm size, Herfindahl–Hirschman index, Lerner index (Gilbert 2006). As argued earlier, these metrics are shown to be imperfect, which is why this work employs a new text-based measure known as *product market fluidity*, developed by Hoberg *et al.* (2014). Authors define product market fluidity as a "measure of the competitive threats faced by a firm in its product market that captures changes in rival firms' products relative to the firm". Product market fluidity is constructed using computational linguistics to analyze firm's 10–K statements, specifically an obligatory part with the description of firm's products. This measure is dynamic and is arguably superior compared to those previously mentioned. Additionally, the study will employ a new measure by Boone (2008), known as *profit elasticity.*

Finally, in order to better capture the shape of the relationship between competition and innovation, this work will draw upon the developments in Lind & Mehlum (2010), employing so–called intersection–union test of U–shape relationship, as well as other empirical techniques and testing procedures.

The relevant data on fundamentals will be extracted from Compustat database. Data on patents is publicly available on the United States Patent and Trademarks Office and the National Bureau of Economic Research websites. Product market fluidity data is available online due to Hoberg *et al.* (2014).

Outline

1. Introduction
2. Literature Review and Motivation
3. Description of Testable Hypotheses
4. Methodology Description
5. Data and Empirical Findings
6. Endogeneity and Identification Issues Discussion
7. Concluding Remarks

Expected Contribution This work will introduce a qualitatively new method of exploring an otherwise well–documented relationship between level of competition and intensity of innovation on a firm level, dealing with methodological flaws of previous research. To my best knowledge, there is no previous research that would use a text-based measure of competition, similar to product market fluidity, to explore this link, therefore this thesis will contribute towards resolution of the fundamental question of competition–innovation relationship, pointing the validity of one of the two conflicting paradigms, developed by Arrow and Schumpeter. The resolution of this debate is of immediate importance to policymakers in a field of antitrust regulation, in addition providing a deeper insight into the process of decision–making on a firm level when facing increasing or decreasing product market competition.

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Author Supervisor

Chapter 1

Introduction

> *"Surely, nothing can be more plain or even more trite common sense than the proposition that innovation, as conceived by us, is at the center of practically all the phenomena, difficulties, and problems of economic life in capitalist society."*
>
> — Joseph Schumpeter, *Business Cycles: A Theoretical, Historical, and Statistical Analysis of the Capitalist Process*

Rivalry and innovation are the driving forces of modern society. Acknowledging existence and understanding specificity of interrelation between them is crucial to the decision–making process in many areas. According to Porter (2011), "Rivalry has a direct role in stimulating improvement and innovation...". However, academic research perceives this relationship as much more ambiguous; differences in its shape and strength have profoundly different implications, as pointed out by *e.g.* Hashmi (2013), and any large–scale regulatory or managerial action must take this into account in order to properly fulfill the ultimate goal of fostering innovation and competition.

Theoretical inquiry into the relationship between market structure and innovative capabilities and performance dates back to the seminal foundation, introduced by Schumpeter (1934) and Schumpeter (2013). As summarized by Cohen & Levin (1989), Schumpeter's initial proposition identified monopoly as a market structure which is the most conducive to innovation due to more generous internal financing and reduced uncertainty about ability to utilize *ex post* output of the innovative activity. Given the tremendously important role, which technological change plays in economic development and welfare growth, this proposition posits a necessity of finding an optimal trade–off between the level of rivalry and quality of innovation in the market. In fact, thinking in line with Schumpeter, the benefits in form of allocative, productive and dynamic efficiency, coming with an increase in competition (Ahn 2002), might have blinded regulatory bodies into taking a stance, which can be detrimental to economic growth. Gilbert (2006) concludes that antitrust enforcement actions by the US Department of Justice (DOJ) and Federal Trade Commission (FTC) reflect a judgment that competition is conducive to innovation, and only recently these agencies have started to raise concerns about potential above–mentioned trade–off (Goettler & Gordon 2011).

Following the initial proposition by Schumpeter, formalized by Aghion & Howitt (1992) in so–called endogenous growth model, research on a link between market structure and innovation has grown vastly. Cohen (2010) however notes that the evidence is mixed and, moreover, somewhat skewed towards demonstrating a positive relationship between the variables of interest. Appropriately, Arrow (1962) showed that, under the assumption of exclusive intellectual property rights, a monopoly has lesser incentive to innovate than a company facing competition due to the "replacement effect" (Tirole 1988) or "escape competition effect"; Aghion *et al.* (1998) later offered other conceptual arguments in favor of a positive competition–innovation link, which is another indication of the problem's complexity.

Inconclusive empirical and theoretical evidence led to a necessity of working towards a more sophisticated, comprehensive framework. The most well–known and successful attempt has been performed by Aghion *et al.* (2005), who reconciled endogenous growth model with the replacement effect to arrive at conclusion that the link between competition and innovation can be described through "inverted–U" shape relationship. This framework remains state–of–the–art, founding an empirical support in recent studies (*e.g.* Bos *et al.* 2013 and Peneder & Woerter 2013). Other attempts to methodologically or conceptually improve studies of competition–innovation link include: modern empirical Industrial Organization (IO) approach, which focuses on a single industry and counter–factual natural experiments (Hashmi 2013; Goettler & Gordon 2011); studies in a field of international trade and globalization (Bloom *et al.* 2011; Gorodnichenko *et al.* 2010); corporate finance and industrial organization studies focusing on firm–level data (Ahuja & Katila 2001; Cloodt *et al.* 2006; Stiebale 2013), and others.

Despite the abundance of conceptual and empirical evidence, the subject of competition–innovation relationship remains problematic. Many of the performed studies have been later exposed as methodologically flawed. Gilbert (2006) in his extensive review points out several important aspects, which, if not properly accounted for, may lead to devaluation of the results, such as failure to distinguish between product and process innovation, lack of generality, omitting important controls, inadequate choice of proxy variables for innovative output and level of rivalry, and others. An especially important issue is connected with an inherent endogeneity of market structure, as has been pointed out in *e.g.* Ahn (2002) and confirmed empirically by Geroski & Pomroy (1990). This is normally addressed by using "natural experiments" resulting from policy changes (Aghion *et al.* 2005), but the challenge of dealing with endogeneity problem in the most proper way still remains. In fact, the issue of methodological correctness and comparability is so serious that in 1992 Organization for Economic Co-operation and Development (OECD) has introduced a specially designed document to provide a general framework for studies on the subject. Still, validity of "reduced form studies" in many cases remains questionable (Hashmi 2013), so that in a systematic review of studies, published between 1993 and 2003, Becheikh *et al.* (2006, p.644) conclude that "the innovation process is still poorly understood and the current state of the literature contributes little to improving our understanding of the phenomenon". This leads to a necessity of refining the methodology, including adoption of a new approach towards quantification of competition and innovation.

The objective of this thesis is to produce a robust evidence on the causal link between market structure and innovation. To achieve this purpose, we follow the general specification developed by Aghion *et al.* (2005) and reexamine the relationship between product market competition and innovative efforts of the US firms by applying novel measures of competition. We also perform thorough test of the inverted–U hypothesis and explore the link between innovation and other market structure induced exogenous factors, such as firm's distance to technological frontier, level of technological opportunities and size of knowledge spillovers.

The results contribute to the previous evidence in three ways. First, to our best knowledge, this study is the first one to apply a new measure of product market competition, developed by Hoberg *et al.* (2014), to competition–innovation studies, and the first one to use a measure by Boone (2008) with the US dataset. Section 4.2 elaborates that these measures are conceptually different from typically used price cost margin or concentration ratios in that they better capture the dynamic nature of competitive threats. Second, unlike the majority of previous empirical studies, we apply a thorough procedure to check for presence of the inverted–U shape, including parametric quadratic estimation, graphical exploratory analysis and a formal test, developed by Sasabuchi (1980) and Lind & Mehlum (2010). Finally, this study addresses the issue of endogeneity of competition variable in a novel fashion by using a set of instruments inspired by Hashmi (2013) and Bloom *et al.* (2011).

The rest of the thesis is structured as follows. Chapter 2 contains the description of theoretical and conceptual frameworks, which address the relationship between market structure and innovation, and the review of relevant empirical findings. Chapter 3 defines the testable hypotheses. Methodology and research design are explained in Chapter 4. Chapter 5 contains data descriptions and presents main empirical findings. Discussion of endogeneity issues and further robustness analysis of the results are given in Chapter 6. Finally, Chapter 7 summarizes the findings and contains concluding remarks for the study.

Chapter 2

Motivation and Literature Review

2.1 Market Structure and Innovation: Schumpeterian Hypothesis

Being a powerful driving force behind the economic development, as has been famously shown by Solow (1957), innovative activity is widely supported in managerial and policy actions. Given that social returns from innovations are higher than private (Griliches 1991) and taking into account an inherent uncertainty of Research and Development (R&D) efforts, regulatory bodies assume an especially high level of responsibility towards actions, which seek to promote innovative activity. However, as argued by Gilbert (2006), antitrust enforcing actions are often based on "common knowledge" or "best practices", which might be highly biased. Authors note that out of 109 merger deals, challenged by the US DOJ and FTC between 2000 and 2003, more than 1/3 became subjects of scrutiny due to the perception that increase in level of market power, resulting from a merger, will have an adverse effect on innovation. Given this, academic research on the subject of the relationship between market structure and innovation appears as especially important and urgent.

Modern inquiry into the link between market structure and innovation has been virtually initiated by Schumpeter (2013, p.106), where he states the following:

> [The large–scale establishment or unit of control] has come to be the most powerful engine of progress and in particular of the long–run expansion of total output . . . In this respect, perfect competition is not only impossible but inferior, and has no title to being set up as a model of ideal efficiency. It is hence a mistake to base the

> theory of government regulation of industry on the principle that big business should be made to work as the respective industry would work in perfect competition.

There is a straightforward intuition behind Schumpeter's argument, namely the economies of scale and scope. Based on the research by National Science Foundation, Gilbert (2006) notes that roughly 70% of R&D investments is financed internally, which means higher innovative capability for large entities with significant market power. Henderson & Cockburn (1996) confirmed strong scale and scope effects using the sample from pharmaceutical industry, showing generally more successful outcome of innovative activities, performed by companies with better financial capabilities. Cohen & Klepper (1996) theorize and empirically verify an idea that the relationship between size and innovation output can be tracked to the ability of larger firms to spread the fixed costs of innovation over more units of output. Other justifications of positive relationship between the degree of market power and productivity of innovation include, according to Cohen (2010), easier access of large companies to the external financing, existence of complementarities between R&D and non–manufacturing activities, and others.

Schumpeter's notion of "creative destruction", which he defined as an "industrial mutation . . . that incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one" (Schumpeter 2013, p.81), was adopted and formalized by Aghion & Howitt (1992) in their version of endogenous growth model. The model allows for obsolescence of research as the new invention destroys monopoly rents motivated by the previous invention, and gives two insights about the effect of market structure on innovation: firstly, an increase in monopoly power increases the amount of research in the state of equilibrium (see Proposition 4, Aghion & Howitt 1992, p.20); secondly, drastic innovation (the one which substantially reduces inventor's monopoly price) will more likely be implemented by the newcomers, rather than by the incumbent producers (Aghion & Howitt 1992, p.7).

Unfortunately, as argued by Hashmi & Biesebroeck (2010)—and this applies to the discussion in the following sections as well—the relationship between competition and innovation is monotonic only under some specific (and possibly rather restrictive) assumptions. These assumptions include type of innovation (product or process), regime of intellectual property rights (exclusive or non–

exclusive), dynamics and degree of certainty of innovation, *ex ante* degree of competition, force of impact of innovation (drastic or non–drastic), and others (see Gilbert 2006; Cohen 2010). For example, Greenstein & Ramey (1998) test the predictions of the model, similar to Aghion *et al.* (1998), under different consumer preferences and arrive at a conclusion, that monopoly can benefit more from innovation, if consumers strictly prefer new product to the old one. Boone (2001) shows that dominant firm has better incentive to innovate and higher probability to retain its superior position in conditions of aggressive competition. Harris & Vickers (1985) argue along the same line that incumbent firm's incentive to innovate is particularly strong because of "preemptive R&D", that is an effort to block newcomers from leapfrogging it. Such diversity is a graphic evidence of difficulty of achieving generality when addressing a link between innovation and competition. In addition, as discussed in the next section, there is a strong theoretical evidence, which directly contradicts the predictions of Schumpeterian hypothesis.

2.2 Market Structure and Innovation: Agency Models and Replacement Effect

Schumpeter's proposition (and subsequent formalization) about a positive relationship between competition and innovation does not find a uniform support in the literature. In fact, Aghion *et al.* (1998) offer several compelling cases in which this link might be opposite (also see Ahn 2002):

1. *Darwinian effect:* under the conditions of increasing competitive pressure, and with the faster rise of overhead costs, companies with agency problems will innovate more in order to avoid bankruptcy and retain solvency. (Porter 2011, p.118) concluded that "active pressure from rivals stimulates innovation as much from fear of falling behind as the inducement of getting ahead".

2. *Neck–to–neck effect:* if the assumption of "leapfrogging" (a tendency of laggard and incumbent firms to switch places frequently), present in several endogenous growth models, is relaxed towards a "step–by–step" innovation, more companies will be in a "neck–and–neck" state (that is, with fairly similar level of technology). Aghion *et al.* (1998) argue, that with

an increase of competitive pressure such companies will have stronger incentive to innovate in order to retain desired level of profits.

3. *Mobility effect:* in a model with "learning by doing", Aghion *et al.* (1998) introduce a distinction between research and development; additionally, they allow mobility rate of laborers between old and new production lines to be endogenous. Authors then show that with the increase in competition incentive to switch to the new lines increase as well, which in turn induces faster product development.

Managerial incentives in connection with innovation–competition link were also studied by Schmidt (1997) and Hart (1983), who argue that the effect of increasing competition is ambiguous: on the one hand, larger number of rivals imply reduced demand and profits for a specific firm, which lowers incentive to innovate; on the other, stronger competition increases the risk of liquidation, which forces managers to react by innovating and decreasing marginal costs. This means that, like the model in Aghion *et al.* (1998), this setup cannot generate robust predictions and does not imply monotony of competition–innovation relationship. In fact, it hints at the "inverted–U" shape relationship, which will be discussed in the next section.

Another well–known theoretical argument in favor of positive link between market power and innovation is the so–called "replacement effect", described by Arrow (1962). Assuming exclusive intellectual property rights, the post–invention incremental profit of a monopolistic entity will be equal to the difference between the post–invention and the pre–invention profits. Since firm, which faces perfect competition, has zero pre–invention profit, it will necessarily have higher incentive to innovate. It then turns out, according to Arrow (1962, p.620), that "the pre–invention monopoly power acts as a strong disincentive to further innovation". This effect can be further aggravated if the outcome of R&D efforts is uncertain. Reinganum (1985) creates a setup, in which the discovery follows an exponential process: investment in R&D increases the probability of successful invention, but does not *per se* guarantee it. Author then shows that the monopoly will have at best the same (and, in general, lower) incentive to innovate as the competitor—if probability of discovery is high for the latter.

From the viewpoint of industrial organization, monopoly (or any entity in possession of market power and large size) might be inferior in terms of innovative potential due to more complex and rigid bureaucracy (Scherer & Ross

1990) or inability of individuals to openly communicate and promote invention up the hierarchical chain. These arguments were in fact acknowledged by Schumpeter himself. Appropriately, Sah & Stiglitz (1984) point out that economic systems, in which several decision–makers undertake projects independently (arguably, such architecture is more typical of smaller entities), are more successful when it comes to selecting and approving projects. In addition, it is likely that the market power can be a detrimental for not only quantity, but also quality of the innovation. For example, Reinganum (1985) and Aghion *et al.* (1998) argue that incumbent firm is likely to make only incremental, or non–drastic discoveries. Christensen (2013) claims that the reason for this behavior is the commitment of large companies to cater to the needs of their existing clients, who do not require radical change in products and services.

It is therefore clear that there is no uniform opinion about the link between market power and innovation. As concluded by Gilbert (2006, p.162):

> Economic theory does not offer a prediction about the effects of competition on innovation that is robust to all of these different market and technological conditions. Instead, there are many predictions, and one reason why empirical studies have not generated clear conclusions about the relationship between competition and innovation is a failure of many of these studies to account for different market and technological conditions.

Not only this, but, as will be shown in Section 2.4, both the Schumpeterian and the replacement effects found a robust empirical support. This brings a need for a more sophisticated framework, which would allow to account for both of these forces. One such attempt has been performed by Aghion *et al.* (2005) and is discussed in the next section.

2.3 Market Structure and Innovation: Inverted–U Relationship

It follows from the previous sections that the effect of competition on innovation is likely non–monotonic. One of the first notions of this appeared in Scherer (1967), who demonstrated positive relationship between employment of scientists and engineers and competition, which becomes less prominent with larger size. Another example of early attempt to analytically infer the "inverted–U" relationship appears in Kamien & Schwartz (1976). As mentioned in Section 2.2, Hart (1983) and Schmidt (1997) developed frameworks, which tie innovation activity with incentive schemes for incumbent, or "satisficing" (Hart 1983) managers, whose utility depends more on being employed rather than on the amount of profits. Threat of liquidation, which rises with the increase in competition, forces them to direct efforts into innovation activity. Aghion *et al.* (1999) employ similar line of thought when allowing for homogeneity among firms and distinguishing between pure profit–maximizing entities and what they call "conservative firms", where adoption of new technologies incur private costs on managerial body. If the economy consists of both types of firms, the effect of increased competition will be twofold and overall ambiguous. However, it has been argued by Aghion *et al.* (2005) that these models, which combine traditional Schumpeterian approach with agency considerations, do not produce robust nonlinear shape of the relationship between competition and innovation.

Such prediction was given by Aghion *et al.* (2001). In a modified model of endogenous growth with gradual catch–up of laggard firms (*i.e.* when leapfrogging is impossible) the effect of Product Market Competition (PMC) on growth turned out to be monotonically positive because of firm's incentive to escape competition by innovating, but for some parameter values it exhibits inverse–U shape, that is it is growth–enhancing up to a certain level of competition, and after that—growth–reducing. Mukoyama (2003) obtains stronger results on inverse–U relationship by assuming more flexible definition of innovation. The model was further addressed and empirically tested in Aghion *et al.* (2005) to obtain a robust evidence. What follows is a short description of the model and its implications.

Economy consists of duopolistic firms with heterogeneous levels of technology. For simplicity, it is assumed that knowledge spillovers occur so that maximum possible gap between technological level of the leader and the laggard is $m = 1$. This means that at any point of time there are sectors of economy, where firms have similar stock of knowledge ("leveled" or "neck–and–neck" sectors, $m = 0$), and those where one firm possesses a technological advantage over the other ("unleveled", $m = 1$). Firms can advance technologically as a result of spillover with Poisson hazard rate h or by investing into R&D with hazard rate $h + n$.

Laggard firms in unleveled sector earn zero profits $\pi_{-1} = 0$, while leading firms earn π_1. Firms in leveled sector are able to collude; if they do, they earn

$\pi_0 = \varepsilon\pi_1$, where $0 \le \varepsilon \le \dfrac{1}{2}$; otherwise, they earn zero profits. PMC is expressed as $\triangle = 1 - \varepsilon$.

The model has a closed–form solution. In the state of equilibrium the research intensity by neck–and–neck firms is defined by Equation 2.1 (see Proposition 1 in Aghion *et al.* 2005, p.714):

$$n_0 = \sqrt{h^2 + 2 \triangle \pi_1} - h \tag{2.1}$$

Research intensity by laggard firm in the unleveled sector (leading firms do not innovate as they cannot increase technological gap m past its current value of 1) is defined by Equation 2.2:

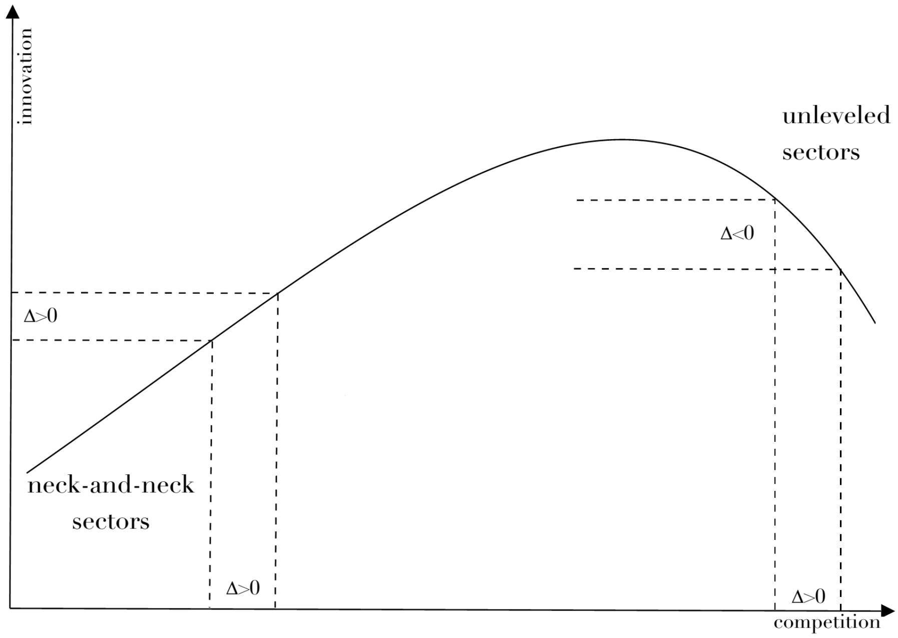
$$n_{-1} = \sqrt{h^2 + n_0^2 + 2\pi_1} - h - n_0 \tag{2.2}$$

It can be shown that n_0 is increasing in $\triangle$, while n_{-1} is decreasing in $\triangle$. Authors proceed by arguing that overall effect of competition on innovation depends on the fraction of leveled and unleveled sectors in the economy. Then, the aggregate innovation rate $\nu(n_0)$ is strictly increasing on the interval $\left[\underline{n_0}, \tilde{n_0}\right]$, where $\tilde{n_0}$ is some local maximum, $\underline{n_0}$ is a condition when firms perfectly collude (competition is minimal); and strictly decreasing on the interval $[\tilde{n_0}, \overline{n_0}]$, where $\overline{n_0}$ is a condition of perfect competition. The shape of the relationship, implied by this setup, is shown in Figure 2.1.

The intuition behind inverted–U relationship is fairly straightforward. First, increase in PMC has a twofold impact on the level of innovation: higher competition implies reduced monopoly rents from innovation, decreasing incentive to innovate—this is the “Schumpeterian effect”, described in Section 2.1; on the other hand, as profits of a leader in unleveled sector are obviously higher, firms will seek to escape from competition, which is achievable by innovating—this behavior was appropriately named the “escape–competition effect” by Aghion *et al.* (2005). In neck–and–neck sector increase in PMC leads to increase in research, as shown in Equation 2.1, while in unleveled sector it leads to decrease in innovation, as shown in Equation 2.2. Then, depending on starting level of competition in the economy, three cases are possible (see Hashmi 2013):

1. *Low competition:* neck–and–neck firms, where escape–competition effect dominates, innovate less and remain leveled; laggard firms, where Schumpeterian effect dominates, innovate more, reducing technological gap and becoming neck–and–neck. As a result, number of neck–and–neck firms

Figure 2.1: Competition and Innovation: Inverted–U Shape



Source: Askenazy *et al.* (2008)

in the economy increases. If PMC rises, innovation intensifies, because escape–competition effect is now stronger economy–wide.

2. *High competition:* similarly, neck–and–neck firms innovate more, and laggard firms—less. As a result, number of unleveled firms in the economy increases. If PMC rises, innovation becomes less active, as Schumpeterian effect now dominates economy–wide.

3. *Moderate competition:* in this case, both types of firms have rather strong incentive to innovate, which means that shares of leveled and unleveled companies in the economy remain roughly unchanged, and the overall level of innovation is the highest.

The model by Aghion *et al.* (2005) makes additional predictions regarding behavior of the firms depending on their relative productivity. Authors define a measure called technological gap, or Distance to Technological Frontier (DTF), which is calculated as the relative difference between Total Factor Productivity (TFP) of the technological leader in the sector and the firm's TFP. They argue that the DTF should increase with the rise in competition, since higher PMC implies a larger number of unleveled firms. The DTF is an important measure of firm's heterogeneity, and its implications for the competition–innovation relationship and incentives to innovate have since been studied in the empirical literature (see Section 2.4).

The model has drawn significant attention in theoretical and empirical IO literature. It has found theoretical support in Tishler & Milstein (2009), Felisberto (2012), Schmutzler (2010) and others. However, as pointed out by Cohen (2010), it has also been criticized for being highly stylized; for example, Gilbert (2006) and Polder & Veldhuizen (2012) question its assumption about step–by–step innovation with only two states of technological capability. Hashmi (2013) argues that solving for general equilibrium in such setup is inappropriate and offers partial equilibrium solution for separate industry, which confirms inverted–U relationship for the UK economy, but not for the US economy. Correa (2012) argues that initial result in Aghion *et al.* (2005) may disappear when accounting for structural brakes in the data. Finally, Polder & Veldhuizen (2012) provide several caveats which point at the difficulties of empirical test of the inverted–U shape (and non–linear relationship in general). Nevertheless, the model from Aghion *et al.* (2005) has been widely used as a benchmark and found a fairly strong empirical support, as will be shown in the next section.

2.4 Previous Empirical Findings

The discussion, initiated by Schumpeter, resulted in a vast amount of empirical research. A summary of studies in "Schumpeterian" tradition is given in, for example, Kamien & Schwartz (1982), Gilbert (2006) and Cohen (2010). As noted by Ahn (2002), studies of the relationship between competition and innovation appeared in "waves", with an increasing quality of data and parameterization. Below we outline main tendencies and findings, focusing on more recent ones and refraining from giving out excessive details, as they can be accessed via above–mentioned reviews.

First attempts to find empirical support of competition–innovation relationship owe to a literal understanding of Schumpeterian argument about prevalence of large business structures in terms of innovative capabilities. Early empirical work is therefore concerned with the link between size and innovation, the latter in majority of cases being measured by R&D expenditures or patent counts. Gilbert (2006, p.187–189) and Cohen (2010, p.132–140) provide an overview of such studies. The earliest attempts were maid by Mansfield (1963) and Scherer (1965), who, working with fairly small samples, did not arrive at a strong monotonic relationship between size and innovation. Later studies, however, as summarized by Kamien & Schwartz (1982), mainly found a positive relationship between size and competition.

Cohen (2010) argues that early empirical studies in Schumpeterian tradition suffered from many methodological drawbacks, namely the use of nonrandom samples and survivorship bias, inadequate control for firm– and industry–level characteristics *etc.* For example, Scott (1984) and Levin *et al.* (1985) found that the relationship between size and innovation disappears when controlling for industry effects or level of appropriability, that is the ability of firms to embody innovation in their products and profit from it. Despite some disagreement in the results, Cohen (2010, p.137) finds it possible to conclude that "the robust empirical patterns relating R&D and innovation to firm size are that R&D increases monotonically—and typically proportionately—with firm size". This consensus has been reinforced in meta–analytical studies by Damanpour (1992) and Camison-Zornoza *et al.* (2004), who found a significant and positive relationship between size and R&D.

Subsequent research approached the relationship between market structure and innovation in a more direct manner. Early studies mostly employed concentration as a (reverse) measure of competition. If there is a significant relationship found (and Becheikh *et al.* (2006) in their systematic review claim that most studies in this area do not produce one), it is mostly positive, as in *e.g.* Mansfield (1986), Nielsen (2001) and Smolny (2003), normally up to a certain threshold of concentration (see Culbertson & Mueller 1985). Some authors found a negative relationship, *e.g.* Blundell *et al.* (1999). A notable "deviation" from tendency of early studies to use concentration as a measure of market power (which is arguably rather flawed, as discussed in Section 4.2) is a study by Geroski & Pomroy (1990), who employed six different measures, such as market share of imports, extent of market penetration by entrants, share of exiting firms *etc.*, and found a negative effect of market power on innovation.

As argued by *e.g.* Cohen (2010), one of the reasons why early competition–innovation studies could not provide very robust results was that they suffered from numerous methodological flaws. Becheikh *et al.* (2006) states that the release in 1993 of "The Oslo Manual" (see OECD 1997) was an important step towards uniformity and applicability of the studies on the subject. Starting from the late nineties authors have begun to employ more appropriate techniques and measures. For example, Nickell (1996) uses price–cost margin (also referred to as mark–up or Lerner Index (LI) after Lerner 1934) as a measure of competition instead of level on concentration, and founds a positive relationship between competition and growth; the same conclusion has been reached by Carlin *et al.* (2004), Hashmi (2013) and Correa & Ornaghi (2014). Gorodnichenko *et al.* (2010), on the contrary, find a negative relationship in the dataset from transition countries. Measures of innovation has evolved as well to better represent innovation *output* rather than *input*. For example, Aghion *et al.* (2005) uses citation–weighted patents to produce the inverted–U relationship for a dataset of UK firms. For a more detailed discussion about appropriate measures of competition and innovation see Section 4.1 and Section 4.2.

Following a landmark work by Aghion *et al.* (2005), who found a robust evidence of the inverted–U relationship, other authors addressed this possible non–linearity as well. Peneder (2012) touches several modern empirical findings in his review. Polder & Veldhuizen (2012) find moderate support for inverted–U hypothesis for a dataset of Dutch companies. Hashmi (2013) shows that the relationship holds for the original dataset, used by Aghion *et al.* (2005), but disappears when tested on the US data, which hints at a possibility that this non–linearity might be highly specific to the industry or the region. Appropriately, Peroni & Ferreira (2012) reject inverted–U hypothesis for the dataset of companies, located in Luxembourg. Gorodnichenko *et al.* (2010) similarly do not find any evidence of inverted–U in transition economies. A study by Bos *et al.* (2013) somewhat stands out from the others by focusing on the sector of financial services, rather than industrial companies. Authors were able to find a robust evidence in support of inverted–U using the dataset from the US banking industry. It is therefore difficult to draw stylized facts about this relationship, but the discrepancy in findings may hint at the superiority of partial equilibrium approach towards modeling of inverted–U shape, which is used by Hashmi (2013), and which applies on an industry–level, and not economy–wide. This kind of research is sometimes called "new IO approach", and it has been gaining popularity recently; one other example is a study by Goettler & Gordon (2011), who found positive relationship between market power and innovation by examining the case of duopolistic market of microprocessors (shared by Intel and AMD).

The notion of DTF, proposed in Aghion *et al.* (2005), and its implications for the incentives of individual firms to perform innovative activity have also been studied in the empirical literature. Apart from the original paper, where authors found that average DTF in the industry increases with the rise in competition, this result has been confirmed by Hashmi (2013). Berube *et al.* (2012)

and Polder & Veldhuizen (2012) approach this relationship from a somewhat different direction, showing that the interaction term between the reverse measure of DTF and proxy for competition is significantly negative. This suggests that, assuming positive effect of competition on innovation, higher DTF reduces firm's incentive to innovate in the situation of rising competitive threats. This introduces additional non–linearity to the competition–innovation link.

The recent years have seen an increased interest in a topic of innovation–competition relationship: new evidence has appeared, as well as new theoretical and methodological advances. In a special issue of *Journal of Industry, Competition, and Trade*, devoted to the developments in competition–innovation studies, Peneder (2012) identifies several features of modern research in this area, such as significant shift in theoretical foundations (which author in part attributes to the findings in Aghion *et al.* 2005, more than once acclaimed in this thesis), new empirical evidence made available by better access to comprehensive micro–data, and development of new measures of competition and innovation. Specific examples include above–mentioned Polder & Veldhuizen (2012) and Peroni & Ferreira (2012). In addition, Berube *et al.* (2012) document a positive impact of increasing competition on R&D expenditures in Canadian firms, while Peneder & Woerter (2013) find an inverted–U relationship in Swiss micro–data. Study by Berube *et al.* (2012) is also unique in the sense that it employs a new measure of competition, developed by Boone (2008), which is discussed in greater details in Section 4.2. Availability of high–quality micro–level data also enables use of subjective measures of competition, as in *e.g.* Tang (2006), and direct measures of innovation, like innovation count.

Following Levin *et al.* (1985) and Geroski & Pomroy (1990), a large body of literature also attempts to clarify the relationship between competition and innovation by employing other exogenous, often market structure induced variables as explanatory. Nieto & Quevedo (2005) contains a very good summary of empirical work which inquires into the explanatory power of three such variables: technological opportunity, or the ease (in terms of time and costs), with which an innovation can be performed in the sector; absorptive capacity, or firm's ability to "identify, assimilate and apply for commercial purposes know–how generated outside of itself" (Nieto & Quevedo 2005, p.1145); knowledge spillovers, or the accumulation of public knowledge from previous innovation. In the empirical study authors document a positive association between R&D expenditures and the first two variables, while spillovers are negatively associated with R&D. Another evidence has been obtained by Askenazy *et al.* (2008), who found that competition affects decision to innovate less when the cost of innovation is high. Finally, Schmookler (1966) shows that patenting behavior is strongly correlated with the effective demand, measured by the investment in capital goods, while Levin *et al.* (1987) presents evidence that propensity to innovate depends on the appropriation mechanisms in the sector.

Research in the field of IO is not the only source of evidence on competition–innovation relationship. A lot of useful insights come from the studies in globalization and international trade. Such studies are usually concerned with the effects of entry of international competitor or change in tariff policies on innovation in the sector. For example, Bloom *et al.* (2011) examines consequences of China joining World Trade Organization (WTO) in 2001 and concludes that competition from Chinese producers led to an increase in R&D and patenting activity in European firms. Bustos (2011) and Teshima (2008) show that reduction of tariffs led to an increase in R&D investments in, respectively, Argentinian and Mexican firms. On the contrary, Gorodnichenko *et al.* (2010) uses data on 27 developing countries to show that increased pressure from foreign competitors reduced innovation.

One more area of research, concerned with competition–innovation relationship, is a field of strategic management, which explores the effect of Mergers and Acquisitions (M&A) and technological alliances on firm's innovative performance. De Man & Duysters (2005) contains a structured review, where authors point out predominantly negative effect of M&A on innovation. However, more recent studies, such as Ahuja & Katila (2001), Cassiman *et al.* (2005), Cloodt *et al.* (2006), Stiebale (2013) and others generally find a positive relationship.

Chapter 3

Hypotheses

The primary purpose of this study is to investigate the relationship between competition, or market structure, and innovation. As has been discussed in Chapter 2, there are conceptual reasons and theoretical evidence in favor of both positive and negative link between the two. The former one is mainly justified by the "Schumpeterian hypothesis" and formalization in endogenous growth model with creative destruction in Aghion *et al.* (1998); the latter can be due to the "replacement effect" as in Arrow (1962), "escape competition effect" as in Aghion *et al.* (2005), or agency problems. In order to determine sign and strength of the relationship this study employs econometric specification similar to Aghion *et al.* (2005) and later empirical studies by Berube *et al.* (2012), Polder & Veldhuizen (2012) and others.

> **H1:** *There is a positive (negative) relationship between product market competition and innovation.*

It has also been shown by Aghion *et al.* (2005) and confirmed by several subsequent empirical studies, that the relationship between competition and innovation can be non–linear due to simultaneous influence of two opposing forces—the "Schumpeterian effect" and the "escape competition effect". In this case the relationship should exhibit so–called inverted–U shape, with competition having positive influence on innovation in concentrated markets, and negative—in highly competitive ones, with the optimal level of competition lying in between.

> **H2:** *There is an inverted–U shape relationship between product market competition and innovation.*

Aghion *et al.* (2005) make additional predictions about the relationship between innovation and technological gap. Gorodnichenko *et al.* (2010) argues that technological gap, or DTF, captures an important heterogeneity in firms patenting and R&D behavior. As discussed in Chapter 2, an expected relationship between innovation and technological gap is positive.

H3: *There is a positive relationship between the distance to technological frontier and innovation.*

Finally, this work explores the effect of other exogenous factors on innovation. Studies by Geroski & Pomroy (1990) and Nieto & Quevedo (2005) define a concept of technological opportunity and theorize that its effect on innovation should be positive as absorbing knowledge from existing technological opportunities increases the chances to successfully innovate.

H4: *There is a positive relationship between level of technological opportunity and innovation.*

Jaffe (1986) and Nieto & Quevedo (2005) identify technological spillovers as another determinant of innovative behavior. In contrast with technological opportunity, spillovers have been shown by previous research to be a disincentive to R&D efforts. Firms operating in the environment of severe technological spillovers will have difficulties in capitalizing on their innovations exclusively; in addition, spillovers induce imitative behavior at the expense of own research.

H5: *There is a negative relationship between level of technological spillovers and innovation.*

Chapter 4

Methodology

4.1 Measuring Innovation

Just like competition, discussed in the next section, innovation is an abstract, non–numerical concept, which is difficult to quantify and measure precisely. For the sake of robustness and completeness this study employs several measures of innovation, which specifics and construction is addressed below.

Traditional measures of innovative activity include those related to innovative inputs and output. Specifically, the most popular variable to capture innovation in the literature is the value of R&D expenditures. Admittedly, this measure is problematic for several reasons, as summarized in Becheikh *et al.* (2006). First, as R&D data includes unsuccessful undertakings, it tends to overestimate actual innovation effort. On the contrary, some innovations occur without explicit R&D as a result of "learning–by–doing" or individual insight. As pointed out by Hagedoorn & Cloodt (2003), R&D activities only partly overlap with (and result in) innovation and patenting, and the degree of this overlap is different in various industries, sectors and geographical regions. Second, R&D measures underestimate innovative performance of small companies due to informality and occasionality of research efforts at such firms (Kleinknecht *et al.* 2002). Third, Sutton (1996) and Kleinknecht *et al.* (2002) argue that precise quantification of R&D efforts, performed by the company, depends on understanding of business units and affiliates hierarchy and geographical structure.

In summary, it is important to understand that the level of R&D expenditures is an *input* to innovation and does not necessarily translate into an actual invention in a predictable, monotonic way. It is, however, an easily accessible measure with high standards of data collection and well understood properties, which is why it is still widely used in competition–innovation studies (for the recent examples see Berube *et al.* 2012, Polder & Veldhuizen 2012, Peroni & Ferreira 2012).

Alternative measures of innovation are connected with firm's patenting activity. Ahn (2002) and Kleinknecht *et al.* (2002) argue that, compared to R&D expenditures, patent data has several features which potentially make it a better indicator. Specifically, this data is based on objective and stable standards, developed in the United States Patent and Trademark Office (USPTO) and European Patent Office (EPO), it is easily accessible on detailed disaggregation level, and allows estimating not only quantitative characteristics of firm's innovative behavior, but also qualitative—based on patent citations. Hirschey & Richardson (2004) provide a good summary of scientific indicators, which are traditionally used in the literature. In this study we employ several measures for the sake of robustness:

1. *Raw patent count:* a number of successful applications for patents to the USPTO in a given time period.

2. *Patent Citation Index (CI):* a number of citations, generated in a given time period by patents, granted to the company in previous periods. The measure can either be absolute or relative to some average citation rate in a given industry. Specifically, we follow Hirschey & Richardson (2004, p.95) in defining CI as "the number of citations generated in the current year by patents granted to the company during the most recent 5–year period".

3. *Citation–weighted patents:* following Aghion *et al.* (2005), we define this measure (on a company–level) as a number of patents, taken out by the firm, weighted by the number of times it has been cited by other patents in its lifetime. This measure is forward–looking, since the data allows calculating *ex post* number of citations. Additionally, we follow Hall *et al.* (2001), who offer a methodology of calculating weights for adjusting citations received for the truncation in later periods.

Hall *et al.* (2001) outline numerous limitations and problems which arise when working with patents and citations data. One such problem is because of truncation: authors show that citations can date back up to 50 years. This means that measuring number of received citations in, for example, 5–year window captures only a small part of them. This issue is mitigated by adjustment for truncation methodology, proposed by authors, but only in part. Another problem is connected with the fact that distribution of patents and citations over years and industries is clearly non–uniform. Authors note a sharp increase in number of patent applications and citations made over time, as well as marked heterogeneity of patenting behavior in different sectors. This can be addressed by controlling for the fixed–effects, but at the same time this approach might conceal a true variation in the data.

There are conceptual problems with patents and patent citations as the measures of innovation activity as well. Becheikh *et al.* (2006) rightly point out that patent data measures inventions rather than innovations. Moreover, data on raw patent counts is, similarly to R&D data, a measure of innovation input, not output. Patents differ greatly in their value and applicability, which is why patenting itself does not necessarily translate into marketable product. Ahn (2002) also notes that not all the innovative activity is patented, but rather gets protection through such means as technological complexity and secrecy. Propensity to patent also varies greatly by industry and firm characteristics, as shown by Kleinknecht *et al.* (2002) and Hall *et al.* (2001). Levin *et al.* (1987) show that in many sectors of the US economy patenting is not considered as the main appropriability mechanism by the firms. Boldrin & Levine (2013) make a rather compelling argument against the patenting mechanism by showing that empirical evidence on patents being conducive to productivity and innovation is very limited. Finally, Belenzon & Patacconi (2013) express concerns with the efficiency of USPTO and show that its decline might have led to the decrease in value of American patents as an indicator of innovative performance.

To address these issues some authors develop an idea of composite metric of patent's scientific merit using factor analysis, or principal component analysis. Hagedoorn & Cloodt (2003) use four variables (R&D expenditures, patent counts, patent citations and new product announcements) to construct an index, which provides a significant reduction of variance. Similarly, Lanjouw & Schankerman (2004) construct a "quality of innovation" variable, which, according to the authors, gives a significant informational gain compared to the usage of any individual measure. This approach, however, leads to the extreme difficulties in interpretation of the results and might raise the problem of overfitting.

4.2 Measuring Competition

One of the most significant contributions of this work lie in the fact that it explores new approaches to the measurement of competition, offered by Boone (2008) and Hoberg *et al.* (2014), and applies them directly in an empirical setting to address the issue of competition–innovation relationship. What follows is the definitions of traditional and novel measures of competition, as well as a brief discussion of their applicability and relevance.

Traditional measure for identification of market structure is a Herfindahl–Hirschman Index (HHI), calculated as follows:

$$HHI_{it} = \sum_{f=1}^{N} s_f^2 \tag{4.1}$$

where s is a market share of firm f, N is a number of firms in the sector, i and t are the indices for, respectively, industry and year. HHI is negatively correlated with the level of competition and can be replaced by measures such as $C4$–ratio or $C8$–ratio—respectively, market share of four and eight largest firms in the economy.

While HHI is still widely used in the studies of competition–innovation relationship, its shortcomings are well recognized in the literature. For example, Ahn (2002) points out that HHI (or similar concentration ratios) "does not reflect competitive pressures coming from potential entrants in a contestable market", that is, this measure is by definition static and does not account for the dynamic aspects of competition. Even more serious issue is emphasized, among others, by Ahn (2002), Gilbert (2006) and Boone *et al.* (2007), and is connected with the fact that even extremely concentrated markets can be highly competitive, and *vice versa*—sectors with high number of participant firms can exhibit a mild competition. Boone *et al.* (2007) demonstrates that level of concentration is highly correlated with the average size of enterprises in the sector, which of course should not be the case for a good measure of competition. Another problem with HHI is described well by Gilbert (2006, p.192):

> ...market concentration is clearly endogenous to innovation. Successful innovation by a market leader can create a firm that competes only weakly with other firms in the industry because it has superior production technology or product quality. Successful

> innovation by a firm that is far from the technological frontier can create new competition by closing the cost or product quality gap relative to the market leader, even though the size structure of the industry may appear to be the same in both cases.

Endogeneity issues are inherent to other measures of competition as well; this issue is addressed in greater details in Chapter 6. Finally, as pointed out by Aghion *et al.* (2005), concentration measures strongly rely on precise definition of market (industry), which might be problematic.

Another popular measure of competition is a Product Market Competition (PCM), or LI, as defined by Lerner (1934). In its general form LI is calculated as follows:

$$LI_{fit} = \frac{P_{fit} - MC_{fit}}{P_{fit}} \tag{4.2}$$

where P is the market price, MC is the marginal cost, f, i and t are the indices for, respectively, firm, industry and time period. Since marginal costs are usually unobserved in the data, the LI is often proxied by the following expression (see *e.g.* Aghion *et al.* 2005 and Askenazy *et al.* 2008):

$$LI_{fit} = \frac{value\ added_{fit} - cost\ of\ capital_t \times capital\ stock_{fit}}{sales_{fit}} \tag{4.3}$$

PCM is essentially a markup of a firm and should be negatively correlated with the level of competition, as competitive pressure drives profits down. Admittedly, it is a superior measure of competition, which does not depend on the definition of market and reflects changes in both company's profits and costs, thereby better capturing both the "escape competition" effect and the "Schumpeterian" effect (Bos *et al.* 2013). As argued by Ahn (2002), however, LI is still far from being a perfect measure of competition. Boone (2008) and Boone *et al.* (2012) outline conceptual difficulties with this construct and provide several theoretical and numerical examples when increase in competition actually leads to increase in the PCM. It is therefore unclear, whether the PCM is non–monotonically related to the level of competition. It is still a popular measure though due to ease of calculation and fairly robust theoretical basis.

Addressing the shortcomings of above–mentioned measures—specifically, of the PCM—Boone (2008) develops a new way to parameterize competition, which he calls Relative Profit Difference (RPD). Generally, RPD is calculated according to Equation 4.4:

$$RPD\left(n, N, I, \theta\right) = \frac{\pi\left(n^{**}, N, I, \theta\right) - \pi\left(n, N, I, \theta\right)}{\pi\left(n^{*}, N, I, \theta\right) - \pi\left(n, N, I, \theta\right)} \tag{4.4}$$

for any $n^{**} > n^{*} > n$, where n is a firm's efficiency, N is an aggregate efficiency index function of individual efficiency levels $n_1 \dots n_I$, I is a set of firms which enter the market, and θ is a parameter which defines how aggressively firm behaves in the market (technically, it is a measure of competition). It can be shown that $RPD(\cdot)$ is increasing in θ.

We omit theoretical details and note that Boone *et al.* (2012) offers an estimation technique for the measure. Specifically, from Equation 4.4 and following Polder & Veldhuizen (2012):

$$\ln\left(\pi_{fit}\right) = \alpha_{it} - \beta_{it} \ln\left(\frac{VC_{fit}}{Y_{ft}}\right) + \varepsilon_{fit} \tag{4.5}$$

or, alternatively, following Berube *et al.* (2012) and Peroni & Ferreira (2012):

$$\ln\left(\pi_{fit}\right) = \alpha_{it} - \beta_{it} \ln\left(AVC_{fit}\right) + \delta_{it} \ln\left(L_{fit}\right) + \varepsilon_{fit} \tag{4.6}$$

where π is a profit, calculated as $\pi_{fit} = Y_{fit} - VC_{fit}$, Y_{fit} is a total value of production (total revenue), VC_{fit} is a total variable cost of production, sum of labor cost and cost of intermediate input, $VC_{fit} = L_{fit} + IV_{fit}$, AVC_{fit} is an average variable cost of production, L_{fit} is a firm's employment to control for size, and estimated coefficient $\hat{\beta_{it}}$ is an estimate of RPD. Practically, it is an elasticity of profit with respect to marginal costs, which is why, following Boone *et al.* (2012), we will further refer to it as the Profit Elasticity (PE).

Authors show that RPD is a theoretically robust measure, which is immune to above–mentioned counterexamples when PCM behaves in improper way (increases with the increase in competition), and is especially superior in concentrated industries. It also properly reacts to the reduced entry barriers, unlike HHI, and inherits best features of PCM, such as independence of market definition and ease of calculation. This is a fairly new measure, which has been used only in a handful of empirical studies (see Berube *et al.* 2012, Peroni & Ferreira 2012 and Polder & Veldhuizen 2012), however, it has already been a subject to some critique, expressed, for example, in Schiersch & Schmidt-Ehmcke (2010). Authors argue that at least in some circumstances PE is an inferior measure of competition compared to PCM, and offer a modified version which accounts for firms' size. As this modification has not been a subject to any testing, we do not present it here.

The last measure of rivalry, which is employed in this study, is developed by Hoberg *et al.* (2014) and known as Product Market Fluidity (PMF). It is a text–based measure, specifically designed to address the dynamic nature of competition. Authors define PMF as a "measure of the competitive threats faced by a firm in its product market that captures changes in rival firms' products relative to the firm". PMF is constructed using computational linguistics to analyze firm's 10–K statements, specifically an obligatory part with the description of firm's products. Formally, PMF is defined as follows:

$$PMC_i = N_{f,t} \frac{D_{t-1,t}}{\|D_{t-1,t}\|} \tag{4.7}$$

where $N_{f,t}$ is firm's f own product description word usage vector, and $D_{t-1,t}$ is an aggregate change vector, which captures changes in usage of a given word j in year t:

$$D_{t-1,t} = \left| \sum_j (W_{j,t} - W_{j,t-1}) \right| \tag{4.8}$$

where $W_{j,t}$ is "an ordered Boolean vector of length J_t identifying which of the J_t words are used by firm f in year t. Element j of $W_{j,t}$ equals one if firm f uses word j in its product description and zero otherwise" (Hoberg *et al.* 2014, p.298). Therefore, intuitively PMF captures changes in both own and competitors' product lines, and increases if the product lines of competitors and the company become more similar—thus, implying higher level of competition. Authors argue that PMF is a more suitable measure to capture product market competition than concentration ratios, as it is forward–looking and has the same desirable properties as PCM and PE (independence of the market definition). In addition, it contains fairly precise information about product market threats since the section with product line description in 10–K statements is required by law to be accurate and up to date. To our best knowledge, this study is the first one to relate PMF to the level of innovation. Since this measure is completely novel, we hope to gain important insights on the relationship between competition and innovation by using it in the regression model. Its properties are further explored in Chapter 5.

4.3 General Framework

To test the link between competition and innovation, this work draws on Aghion *et al.* (2005) and later applications by, for example, Griffith *et al.* (2010), Berube *et al.* (2012), Peroni & Ferreira (2012) and others to estimate, in the most basic form, the relationship in Equation 4.9:

$$I_{fit} = g\left(\mu_{fit}, X_{fit}\right) \tag{4.9}$$

where I is a measure of innovation, μ is a measure of competition, X is a vector of controls, and f, i and t are the indices for, respectively, firm, industry and year.

Features of our dataset allow performing analysis on micro–level, as in Polder & Veldhuizen (2012). Taking into account discussion in Section 4.1 and Section 4.2, we estimate the following equation:

$$\begin{aligned} INNOV_{fit} = \alpha_0 &+ \beta_1 COMP_{fit} \\ &+ \beta_2 COMP^2_{fit} + \varepsilon_{fit} \\ \varepsilon_{fit} &\sim iid(\sigma^2_\varepsilon) \end{aligned} \tag{4.10}$$

where $INNOV$ is a measure of innovation, and $COMP$ is a measure of competition. The squared term $COMP^2$ is included as a simple test of the inverted–U hypothesis: positive sign for β_1 and negative for β_2 would be an evidence of this shape (other approaches to testing for this non–linear relationship are discussed below). As discussed in Chapter 3, there are reasons to expect both negative and positive sign for β_1.

In order to test **H3** and **H5**, we include additional terms into Equation 4.10. First, following Aghion *et al.* (2005), we define DTF for industry i and firm f is calculated according to Equation 4.11:

$$DTF_{fit} = \frac{TFP_{Fit} - TFP_{fit}}{TFP_{Fit}} \tag{4.11}$$

$$TFP_{fit} = \frac{Y_{fit}}{K_{fit} + L_{fit} + IV_{fit}} \tag{4.12}$$

where TFP is a total factor productivity, index F denotes a firm which is a technological leader in the industry, Y is a measure of value–added, K is a cost of capital, L is a cost of labor, and IV is a cost of intermediate input. Therefore, DTF is calculated as the difference between TFP of a firm and the leading (in terms of productivity) firm in the industry. Following previous studies, we use the 95^{th} percentile of TFP_{Fit} to account for extreme outliers.

In order to measure knowledge spillovers, we follow Nieto & Quevedo (2005) and calculate the stock of spillovers relative to total R&D in the sector:

$$SP_p = \sum_{\substack{f=1 \\ f \neq p}}^{n} R\&D_f - R\&D_p \tag{4.13}$$

Finally, we follow Nieto & Quevedo (2005) and calculate a proxy for technological opportunity. The dummy variables for the companies with the different level of Technological Opportunity (TO) are created according to Berube *et al.* (2012), who uses modified version of taxonomy, introduced in Pavitt (1984). This method classifies companies into five buckets according to Appendix A. We can now rewrite specification in Equation 4.10 to obtain the main model:

$$\begin{aligned} INNOV_{fit} = \alpha_0 + \beta_1 COMP_{fit} &+ \beta_2 COMP_{fit}^2 + \beta_3 DTF_{fit} \\ &+ \beta_4 COMP_{fit} \times DTF_{fit} + \beta_5 SP_{fit} + \delta z + \varepsilon_{fit} \\ \varepsilon_{fit} \sim iid(\sigma_\varepsilon^2) \end{aligned} \tag{4.14}$$

where the interaction term $COMP \times DTF$ is included following Peroni & Ferreira (2012), and δz is a set of control variables. δz vector includes: number of employees as a proxy for firm's size; amount of short–term and long–term debt; Return on Investment (ROI) as a measure of profitability. Theoretical relationship between firm's size and level of innovation is discussed in Section 2.1. According to Bos *et al.* (2013), level of debt may have either positive or negative influence on innovation: on the one hand, firms with high debt pressure innovate to generate income and decrease the threat of liquidation, as discussed in Section 2.2; on the other, high interest payments reduce free cash flow, available for investments into R&D. Finally, following, for example, Audretsch (1995), we expect an overall positive effect of increase in profitability on innovative output.

Depending on the measure which enters left–hand side of Equation 4.14, a special treatment might be required to account for the nature of count data, such as patent and citations counts. Aghion *et al.* (2005) use Poisson regression, but Hashmi (2013) argues, that, given statistical properties of patent counts and patent citations, specifically a phenomenon known as overdispersion, a

Negative Binomial (NB) model is more appropriate as it relaxes the assumption of mean and variance equality in Poisson regression. In this case innovation relates to competition according to Equation 4.15:

$$g\left(p_i \mid x_i, \nu_i\right) = \frac{e^{-\lambda_i \nu_i}\left(\lambda_i, \nu_i\right)^{p_i}}{p_i!} \tag{4.15}$$

where p is a measure of innovation, λ is the conditional mean, x is a set of industry and year controls, and ν is an error term, which is assumed to follow Gamma distribution with mean 1 and variance α:

$$g\left(\nu\right) = \frac{\nu^{\frac{1-\alpha}{\alpha}} e^{-\frac{\nu}{\alpha}}}{\alpha^{\frac{1}{\alpha}}\Gamma\left(\frac{1}{\alpha}\right)} \tag{4.16}$$

Additionally, as discussed in Section 5.2, the data on both R&D expenditures and patents is a subject to peculiarity, known as inflated zeros, which translates into a large number of confirmed (non–missing) zero observations. This issue can be addressed by employing so–called zero–inflated NB model, first considered by Greene (1994). Section 5.2 tests this specification and provides a check of its applicability using Vuong likelihood ratio test.

The parametric quadratic specification in Equation 4.14 is commonly used to test for the inverted–U relationship—not only in IO studies to explore competition–innovation link, but also in such economic applications as testing for Kuznets and Laffer curves. This study uses several different methods to confirm or reject the inverted–U relationship between competition and innovation. First, Lind & Mehlum (2010) develop a formal test for the presence of inverted–U shape. Intuitively, this test should confirm (reject) that the slope of the curve is positive at the beginning and negative at the end of some interval of values of x–variable (measure of competition), for example $[\min\left(x\right), \max\left(x\right)]$. The testing procedure is known as *intersection–union test* and is based on Sasabuchi (1980). Second, we utilize piecewise regressions by quartiles of competition measure in order to explore sign and strength of the relationship between dependent and independent variable in greater details. Finally, a simple exploratory graphic analysis provides useful insights as well.

Chapter 5

Data and Empirical Results

5.1 Data and Summary Statistics

This study uses several primary data sources, summarized in Table 5.1. The data on patent counts, patent citations and truncation adjustment factors is obtained from National Bureau of Economic Research (NBER) Patent Data Project webpage[1]. The data is for years 1976–2006 and captures all the successful patent applications, forward and backward references, granted by the USPTO in a given period, which amounts to around 3 million patents and 24 million citations. A thorough analysis of the database (albeit for a shorter period of 1975–1999) and the discussion about applications is given in Hall *et al.* (2001).

The data on patents and patent citations is matched to the accounting data using the unique company identifier *gvkey*, resulting in 185,042 firm–year observations in a dataset of 18,412 US traded companies, however, only the timespan of 1990–2013 is used in the full specification regressions due to the limited availability of data, needed to calculate the DTF, resulting in a subset of 116,197 firm–year observations and 13,662 companies. Following previous studies, firms in the financial sector (Standard Industrial Classification (SIC) codes 6000–6999) and regulated utilities (SIC codes 4900–4999) are excluded from the sample; all the specifications were tested on the subset of manufacturing firms only (SIC–2 codes 20 to 39) and produced results, similar to those below. We also drop firms with missing (or negative) assets, sales, number of employees or gross Property, Plant and Equipment (PP&E). Missing observations of R&D expenditures are recoded as zeros (this produces very similar regression results

[1] Available at http://www.nber.org/patents/.

Table 5.1: Main Data Sources

Source	*Period*	*Variables*
Compustat	1975–2014	R&D, Employees, Sales, Operating Profit & Expenses, Capital, Assets, Debt, SIC, NAICS
NBER Patent Data Project	1976–2006	Patent Counts, Citations, Truncation Factor, HJT Technological Classification
Hoberg–Phillips Data Library	1997–2013	Product Market Fluidity, HHI
OECD Statistics	1990–2013	Average Annual Wages in Manufacturing Sector
Bureau of Economic Analysis Database	1975–2014	Price Indices (Deflators)
UN Comtrade Database	1990–2013	Chinese and World Exports to the US
Peter Schott's Database	1990–2013	Tariff Rates, Freight Rates

compared to a sample, where such observations are dropped; the issue is discussed in more details below). Summary statistics for the resulting dataset on main variables, used in this study, are shown in Table 5.2. Summary for the subperiods of 1990–2001 (a timespan, used in estimations with patent data) and 2002–2014 is presented in Table B.1 and Table B.2.

Table 5.2: Summary Statistics: 1990–2014

Variable	*Mean*	*Std. Dev.*	*Min.*	*Max.*	*N*
R&D Expenses	1.31	1.83	0	9.55	116197
Number of Patents	13.44	100.52	0	4344	54527
Number of Citations (5–year)	196.09	1703.33	0	104907	54527
Citation–Weighted Patents	67.52	525.48	0	28603	42638
HHI	0.06	0.02	0.03	0.25	74969
LI	0.95	0.07	0.08	1	116197
PE	5.66	3.26	0.02	33.32	101914
PMF	6.81	3.54	0	27.59	56351

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Table 5.2 – *Continued from previous page*

Variable	*Mean*	*Std. Dev.*	*Min.*	*Max.*	*N*
DTF	0.26	0.22	0	1	116197
Spillovers	6.43	4.18	-9.48	12.29	116197
Number of Employees	6.67	2.3	0	14.6	116197
Debt–to–Equity	0.21	0.19	0	0.98	116197
ROI	-0.03	0.52	-3.85	0.81	116197

Notes: R&D expenditures and number of employees are taken in natural logs. PE coefficient, as obtained from the the regressions, is multiplied by -1. The measure of knowledge spillovers is transformed using inverse hyperbolic sine transformation.

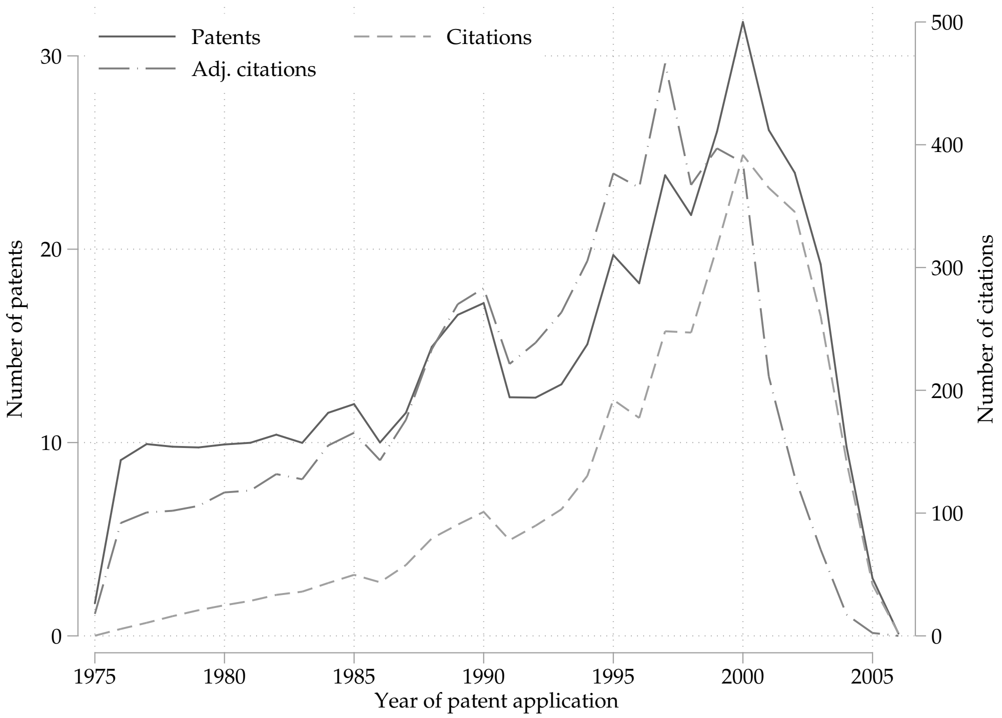
In each case we use the year of application, filed by assignee to the USPTO, when calculating patent and citations statistics. Application year, unlike a year in which patent was actually granted, is a more relevant time measure due to a large lag between application and subsequent decision by the USPTO, with around 73% of all patents in the sample being granted within 2 years after submission.

The data on patents and citations is highly non–stationary across years and, to some extent, technological sectors, as can be clearly seen on Figure 5.1, Figure B.1 and Figure B.2. The pictures demonstrate truncation problem, discussed earlier, which cannot be fully mitigated by using adjustment factors from Hall *et al.* (2001) (see Figure 5.1). Because of this, the study follows Correa & Ornaghi (2014) in restricting the data to 1975–2001 period when using patent data in regressions.

Data on PMF and HHI is obtained from Hoberg–Phillips Data Library[2]. We use fitted HHI, with estimation procedure described in Hoberg & Phillips (2010). This measure is positively and significantly correlated with the HHI, calculated from the raw data, but, in our view, better captures the degree of concentration, as the "raw" HHI completely omits non–traded firms from comparison. For the PMF averages by industry and period are presented in Table B.3. PMF measure is arguably different from other proxies of competition, with correlation coefficients not exceeding 0.3 in absolute values, which indicates its novelty and hints on the possibility of drawing useful insights from regressing innovation measures on it. Another measure of competition—PE as per Boone (2008)—is calculated according to Equation 4.6 and presented in

[2]Available at http://cwis.usc.edu/projects/industrydata/.

Figure 5.1: Average Number of Patents, Citations and Adjusted Citations per Assignee



Notes: Only those US traded companies included, for which a definite match with patent data has been obtained (including definite matches with zero patents or citations).
Source: NBER Database, Compustat, author's calculations.

Table B.4. The observations for which β_{it} is negative (which would imply that increase in variable costs leads increase in profits) are dropped: we lost less than 1% of firm–year observations because of this.

Finally, in order to calculate TFP and DTF, we refer to the data on annual wages from OECD[3] to calculate cost of labor as an average annual wage in the manufacturing sector multiplied by the number of employees in the company (while Compustat database provides similar information in *xlr* item, it is disclosed only for a small number of observations). Sales and capital stock are taken in real terms, deflated by respective indices from Bureau of Economic Analysis database[4]. Construction of this and other variables, used in the study, is discussed in greater details in Table C.

[3]Available at http://stats.oecd.org/.
[4]Available at http://www.bea.gov/.

5.2 Main Findings

5.2.1 Basic Relationship

This section outlines the main results of empirical testing of competition–innovation relationship. We start by estimating the simplest specification as in Equation 4.10. Unlike in Aghion *et al.* (2005), the level of data disaggregation allows performing estimation on firm level: in this we follow recent studies by *e.g.* Berube *et al.* (2012), Correa & Ornaghi (2014) and others. Throughout this section we focus only on the most theoretically sound measures of innovation and competition, reporting full results in the appendices. Table 5.3 outlines the results of simple regression with quadratic terms included as the first test for non–linearity.

Table 5.3: Competition and Innovation: Basic Specification

	(1) R&D	(2) Patents	(3) Patents (weight.)	(4) CI
Employment	0.0197	0.200***	0.236***	0.250***
	(0.83)	(7.98)	(11.23)	(11.74)
$Employment^2$	0.0232***	-0.000772	0.00401**	-0.00443**
	(10.12)	(-0.49)	(2.99)	(-3.28)
Constant	-0.166**	-1.239***	-3.421***	-1.944***
	(-2.80)	(-12.86)	(-43.04)	(-24.25)
Observations	185449	56333	54993	52199
R^2	0.142			
HHI	-17.08***	-12.44***	-0.426	-20.49***
	(-11.72)	(-10.88)	(-0.40)	(-19.69)
HHI^2	67.78***	62.32***	26.45***	101.7***
	(8.93)	(11.23)	(4.84)	(20.18)
Constant	1.806***	0.778***	-1.539***	0.484***
	(30.49)	(15.40)	(-35.35)	(10.70)
Observations	133127	51867	50740	48212
R^2	0.015			
LI	-0.0786	1.317	12.47***	-3.827**
	(-0.11)	(0.93)	(8.28)	(-3.08)
LI^2	0.269	0.00460	-7.180***	3.516***

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Table 5.3 – *Continued from previous page*

	(1)	(2)	(3)	(4)
	(0.69)	(0.01)	(-8.48)	(5.01)
Constant	0.945**	-0.946	-6.804***	0.153
	(3.07)	(-1.50)	(-10.18)	(0.28)
Observations	185449	56333	54993	52199
R^2	0.001			
PE	0.0213***	0.0798***	0.0938***	0.134***
	(7.83)	(9.85)	(10.77)	(16.08)
PE^2	-0.00062***	-0.00317***	-0.00473***	-0.00493***
	(-6.02)	(-6.90)	(-9.22)	(-10.26)
Constant	1.084***	-0.0582	-1.813***	-0.898***
	(95.29)	(-1.80)	(-55.70)	(-28.09)
Observations	160940	49714	48602	46086
R^2	0.001			
PMF	-0.00347	-0.0357*	-0.0703***	-0.0618***
	(-0.64)	(-2.04)	(-3.57)	(-3.88)
PMF^2	0.000765**	0.00216*	0.00292*	0.00292***
	(3.11)	(2.45)	(2.58)	(3.44)
Constant	1.520***	1.469***	-0.797***	1.136***
	(61.92)	(17.66)	(-10.38)	(15.95)
Observations	56381	8936	8382	8838
R^2	0.002			

Notes: Specifications (2)–(4) are estimated for the subsample of 1975–2001 with negative binomial panel data regression. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results in Table 5.3 appear to be somewhat mixed. Size of the firm, proxied by the number of employees, has a positive influence throughout all the measures of innovation used, in line with Schumpeterian argument, however, altogether decrease in competition seems to be mostly associated with the decrease in innovation, as evidenced by negative signs for the HHI measure, and positive—for PE measure. The latter appears to be the most robust measure of competition in all four specifications tested, additionally demonstrating a clear non–linearity, as the quadratic term has an opposite sign and high significance. These findings are further explored in the next subsection using a full specification from Equation 4.14.

5.2.2 Full Specification and Key Findings

The full model regression results are reported according to Equation 4.14. We perform a firm–level panel data regression of the main innovation input and output measures, such as R&D expenditures, patent count, citation–weighted patents and citation index, on key competition measures, specifically HHI, LI, PE and PMF. Following Hashmi (2013), count data (such as patents and citations data) is modeled using negative binomial regression—a generalization of Poisson model with relaxed assumptions about distribution moments—in order to account for apparent overdispersion in the data. Every regression equation includes firm and year fixed effects: Hausman specification test was performed to confirm that in each and every case fixed–effects panel model is preferred to random–effects. As argued in Section 4.1, R&D expenditures and citation–weighted patents are the most theoretically robust and frequently employed measures of innovation despite some obvious drawbacks. We therefore center the following discussion around specifications with these variables and report respective empirical results Table 5.4 and Table 5.5, while the rest of the results are shown in Appendix D.

Table 5.4: Competition and Innovation: R&D Expenditures

	(1)	(2)	(3)	(4)
HHI	-7.605***			
	(-5.08)			
HHI^2	21.97***			
	(3.56)			
LI		0.855		
		(1.17)		
LI^2		-0.721*		
		(-1.66)		
PE			-0.00806**	
			(-2.41)	
PE^2			0.0000428	
			(0.38)	
PMF				0.0111**
				(2.15)
PMF^2				-0.0000662

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Table 5.4 – *Continued from previous page*

	(1)	(2)	(3)	(4)
				(-0.28)
DTF	0.304***	-0.505	0.172***	0.305***
	(3.56)	(-0.76)	(3.72)	(4.77)
Spillovers	-0.0286***	-0.0402***	-0.0203***	-0.0516***
	(-3.21)	(-5.84)	(-2.63)	(-6.82)
Employment	0.304***	0.298***	0.317***	0.349***
	(28.31)	(30.27)	(30.00)	(25.41)
Debt	-0.0957***	-0.0683***	-0.0953***	-0.0662*
	(-3.37)	(-2.62)	(-3.41)	(-1.94)
ROI	-0.0397***	-0.0436***	-0.0451***	-0.0398***
	(-6.09)	(-7.66)	(-7.50)	(-4.77)
$DTF * Comp$	1.734	0.900	0.0287***	0.000890
	(1.04)	(1.34)	(4.37)	(0.15)
Constant	-0.338***	-0.822**	-0.748***	-0.736***
	(-3.23)	(-2.56)	(-8.90)	(-6.79)
Observations	74969	116197	101914	56351
R^2	0.156	0.160	0.174	0.184
Hausman	3760.63	6392.47	5030.77	4681.83
p–value	0.00	0.00	0.00	0.00

Notes: Dependent variable is R&D expenditures. Standard errors are Huber–White robust errors. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5.4 reports coefficients of fixed–effects panel data regression with robust standard errors of R&D expenditures on different measures of competition. Coefficients on HHI, LI and PMF have expected signs, and the results indicate a strong positive link between competition and incentive to innovate based on market concentration measure. In addition, an opposite sign on squared HHI term points out a non–linear relationship between the two variables. This and all the following specifications also clearly demonstrate that propensity to innovate increases with the size, as proxied by employment (although not necessarily monotonically, as the regressions—which are not reported—with the squared term of logarithm of employment included show a significant negative coefficient).

Table 5.5 reports the results of the similar specification with citation–weighted patents—the preferred measure of innovation in this study, in line with Aghion *et al.* (2005), Hashmi (2013), Correa & Ornaghi (2014) and others. The model employed is negative binomial panel data regression with firm and year fixed effects: Hausman specification test results confirm adequacy of selecting fixed effects over random effects. In the table negative binomial model is also compared with panel data Poisson regression; however, comparison of Akaike and Bayesian information criteria, as well as Pearson dispersion coefficients from GLM estimation and over–dispersion parameters from cross–sectional negative binomial regressions (not reported), strongly suggests that Poisson model is not adequate due to apparent overdispersion of the dependent count variable.

Table 5.5: Competition and Innovation: Citation–Weighted Patents

	(1)	(2)	(3)	(4)
HHI	-4.257**			
	(-2.20)			
HHI^2	23.38***			
	(2.62)			
LI		14.75***		
		(6.45)		
LI^2		-9.961***		
		(-7.42)		
PE			0.128***	
			(8.00)	
PE^2			-0.00671***	
			(-7.94)	
PMF				0.0164
				(0.80)
PMF^2				-0.00138
				(-1.10)
DTF	1.464***	-18.94***	1.130***	0.0449
	(7.07)	(-9.74)	(6.82)	(0.16)
Spillovers	0.0605***	0.0550***	0.0741***	0.0561***
	(16.16)	(16.28)	(17.06)	(8.40)
Employment	0.332***	0.335***	0.321***	0.325***
	(51.23)	(54.68)	(51.01)	(25.02)
Debt	-0.392***	-0.308***	-0.382***	-0.312***

Continued on next page

Table 5.5 – *Continued from previous page*

	(1)	(2)	(3)	(4)
	(-5.97)	(-4.82)	(-5.72)	(-2.72)
ROI	0.148***	0.153***	0.171***	0.233***
	(5.08)	(5.33)	(5.74)	(4.82)
$DTF * Comp$	-11.45***	20.39***	-0.0247	0.0756***
	(-2.81)	(10.41)	(-0.78)	(2.95)
Constant	-4.150***	-9.321***	-4.874***	-3.668***
	(-40.30)	(-9.69)	(-47.90)	(-24.03)
Observations	24270	25771	23282	8374
Hausman	1523.91	2729.86	4951.57	828.06
p–value	0.00	0.00	0.00	0.00
AIC	*yes*	*yes*	*yes*	*yes*
BIC	*yes*	*yes*	*yes*	*yes*

Notes: Dependent variable is citation–weighted patents. Coefficients are obtained from negative binomial panel data regression. Estimation is for the subsample of 1975–2001. AIC and BIC fields spell "*yes*" if negative binomial model is preferred to Poisson regression. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The regression results strongly confirm positive relationship between competition and innovation outcomes. All the coefficients for measures of competition, except of PMF, are significant and have expected signs. Moreover, in each case we witness a switch of sign for quadratic term, which may indicate a presence of inverted–U relationship. The results for other patent–related measures of innovation are qualitatively similar and reported in Appendix D, suggesting that firms in less concentrated, more competitive markets are more likely to produce meaningful innovative output. In addition, we also directly address the issue of extreme skewness of count data by employing so–called zero–inflated negative binomial models, which are designed to account for the large number of zero patent and citations observations in the data; Vuong test confirms presence of the inflation problem. The results are reported in Table D.3, Table D.4 and Table D.5: the findings appear to be fairly robust to this change in specification. As in previous case, likelihood–ratio test confirms superiority of zero–inflated negative binomial model compared to zero–inflated Poisson.

Control variables, included in the regression, appear to be highly sensitive to the choice of specification. Thus, we were not able to obtain robust evidence on the effect of knowledge spillovers and ROI on innovation, as coefficients for both variables are highly significant in specifications with R&D expenditures and citation–weighted patents, but have opposite signs. The former issue might be due to the problems in measurement of spillovers: since the dataset includes only publicly traded firms, the true level of spillovers, affected by private–held companies and foreign competitors as well, might be concealed. On the other hand, the results mostly confirm the statement, expressed in **H3**, showing a positive association between DTF and R&D expenditures. We also report the results of simplified panel data regressions of measures of innovation on DTF and spillovers in Table 5.6, this time finding a negative and significant association of the latter with R&D and patent variables. An interaction term $DTF * Comp$ is primarily positive, which, contrary to the results in Berube *et al.* (2012), suggests that higher competition increases positive effect of DTF on firm's incentive to innovate. Finally, the level of debt has a clear negative association with the level of innovation, rejecting the "threat of liquidation" hypothesis.

Table 5.6: DTF and Knowledge Spillovers: Relationship with Innovation

	(1) R&D	(2) Patents	(3) Patents (weight.)	(4) CI
DTF	0.0813**	-0.0151	-0.419***	-0.183***
	(2.51)	(-0.27)	(-8.39)	(-3.90)
Constant	1.021***	0.367***	-1.320***	-0.320***
	(65.04)	(10.83)	(-37.56)	(-9.73)
Observations	116197	26744	25771	25486
R^2	0.061			
Spillovers	-0.0257***	-0.0204***	0.00825***	-0.0295***
	(-3.59)	(-7.33)	(3.46)	(-11.35)
Constant	0.796***	0.0401	-1.785***	-2.220***
	(25.93)	(0.45)	(-18.74)	(-12.62)
Observations	185042	56167	54826	52075
R^2	0.076			

Notes: Standard errors are Huber–White robust errors. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Testing of **H4** requires changes in specification. It is not possible to directly include the dummies for TO into the regression equations as in Table 5.5 due to their perfect collinearity with firm fixed effects, therefore Table 5.7 presents coefficients for TO dummies for simple negative binomial regression with year fixed effects and standard errors clustered on *gvkey*. Specification is the same as in Equation 4.14, with citation–weighted patents as depended variable and irrelevant coefficients. Results indicate that the influence of TO is large and significant, with firms in more research–oriented sectors producing comparably more innovative output. Results for the specifications with different measures of innovation are qualitatively similar. ANOVA strongly rejects the null of equal conditional means in all TO groups.

Table 5.7: Technological Opportunity: Regression Coefficients and Significance

	HHI	*LI*	*PE*	*PMF*
Resource–intensive	0.236	0.683	0.695	0.572
	(0.47)	(1.55)	(1.40)	(1.37)
Labor–intensive	-0.339	-0.251	-0.127	0.105
	(-1.18)	(-0.92)	(-0.46)	(0.45)
Scale–intensive	0.427	0.708**	0.798**	0.893***
	(1.28)	(2.32)	(2.39)	(3.12)
Science–based	1.387***	1.762***	1.674***	1.739***
	(4.33)	(5.93)	(5.11)	(6.35)
Specialized	0.152	1.080***	0.732**	1.121***
	(0.45)	(2.60)	(2.17)	(3.71)
Observations	36827	39812	35867	14326
Wald test	59.41	82.31	66.63	56.31
p–value	0.00	0.00	0.00	0.00

Notes: Dependent variable is citation–weighted patents. Coefficients are obtained from negative binomial regression, with irrelevant coefficients omitted. Estimation is for the subsample of 1975–2001. Wald test has the null of joint insignificance of regression coefficients. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We next address the issue of insignificant coefficients on the PMF measure when regressed against patent data as the measure of innovation. Referring to Hoberg *et al.* (2014) it is possible to conclude that PMF is a special measure, which drastically differs from all the other ones employed in this study. One possible explanation of the discrepancy between the expected and actual results lies in extreme skewness of our data, which manifests in a large number of zero observations of R&D expenditures, patent counts and patent citations. It is likely that regression coefficients on fluidity are heavily influenced by these observations because, unlike for other measures of competition, the causal link between PMF and innovative effort might be weak, as mentioned in Hoberg *et al.* (2014). Essentially, there are two possible causes of changes in PMF: firstly, the company itself can introduce changes to its product line, which will lead to increased or decreased similarity with competitors' products and, consequently, increase or decrease in PMF; alternatively, fluidity may change because of the changes in competitors' product lines, without any effort from the firm's side. This means that the company might abstain from any research and still face large changes in rivalry, as measured by PMF. While this is quite possible in case of LI and PE as well due to new entries, acquisitions, divestitures *etc.*, mark–up and profit elasticity are more heavily affected by internal processes.

We address this potential issue by accounting for zero observations of the dependent variable. In case of R&D expenditures we drop all zero observations; for patent and citations data, we draw upon *e.g.* Czado *et al.* (2007) and employ zero–inflated negative binomial model. As discussed in Section 4.3, this specification assumes that all the firms in the sample belong to one of the two groups: those, for which innovative output is always equal to zero and cannot be affected by any exogenous factors; and those, for which innovation process depends on exogenous factors, yet zero innovation is still possible under a specific combination of external conditions. This assumption is not overly restrictive, as evidenced by the transition matrix in Table 5.8: firms with low R&D are unlikely to initiate research in future as, for example, company in the bottom quartile in terms of R&D expenditures has only 7.5% total probability of moving into higher quartiles with time.

Table 5.8: Transition Probabilities Matrix: Percentiles of R&D

	25^{th}	50^{th}	75^{th}	100^{th}
25^{th}	92.50	7.14	0.31	0.05
50^{th}	5.82	83.45	10.58	0.15
75^{th}	0.25	6.06	84.46	9.23
100^{th}	0.25	0.10	4.39	95.47

Table 5.9 presents the results of these modified regressions. We use a dummy variable, based on the level of employment, as the selection equation for zero

inflation: it takes value of 1 if the number of employees exceeds 500 (which is an accepted threshold to define business as large in the US). We experimented with other variables, based on the value of total assets, age and profitability indicators, obtaining very similar results. For the majority of specifications accounting for zero observations had a clear positive effect on PMF regression coefficients. Similarly to other measures of competition, increase in PMF is associated with increase in innovative performance. Additionally, we study lagged values of PMF and found them to be positive and significant in most specifications, which means that magnitude of the overall effect of increase in fluidity on innovations is likely economically significant, but stretched in time. Similar results are presented in Table D.3, Table D.4 and Table D.5, showing a likely non–linear association between the variables.

Table 5.9: Product Market Fluidity and Innovation: Adjustment for Zero Observations

	(1) R&D	(2) Patents	(3) Patents (weight.)	(4) CI
PMF	0.0105***	0.0432	0.0956**	0.111***
	(3.38)	(1.38)	(2.10)	(3.19)
PMF_{t-1}	0.00888***	0.0136	0.0290	-0.000450
	(4.98)	(0.61)	(0.94)	(-0.01)
PMF_{t-2}	0.00928***	0.0864***	0.0990**	0.151***
	(4.24)	(3.04)	(2.20)	(4.08)
DTF	0.451***	1.300**	2.691***	2.580***
	(5.92)	(2.20)	(3.13)	(3.61)
$DTF * Comp$	-0.00380	-0.00593	-0.290***	-0.226***
	(-0.58)	(-0.12)	(-4.13)	(-3.72)
$Spillovers$	-0.0238***	0.0955***	0.0581***	0.0796***
	(-4.07)	(6.02)	(2.74)	(4.40)
$Employment$	0.621***	0.897***	0.740***	0.844***
	(35.54)	(30.22)	(17.48)	(24.70)
$Debt$	-0.0582	-1.359***	-1.884***	-1.630***
	(-1.31)	(-4.84)	(-4.79)	(-4.92)
ROI	-0.0497***	0.267***	-0.111	-0.173*
	(-4.03)	(2.80)	(-0.81)	(-1.74)
Constant	-1.491***	-6.550***	-1.878***	-4.906***

Continued on next page

Table 5.9 – *Continued from previous page*

	(1)	(2)	(3)	(4)
	(-11.20)	(-21.28)	(-4.22)	(-13.19)
Inflation				
Emp.dummy		4.391***	-0.402***	3.756***
		(34.95)	(-8.29)	(13.34)
Constant		-5.490***	0.299***	-5.540***
		(-286.08)	(7.14)	(-136.43)
Alpha				
Constant		1.248***	0.969***	1.363***
		(23.40)	(12.10)	(28.30)
Observations	21849	6497	6497	5427
R^2	0.445			

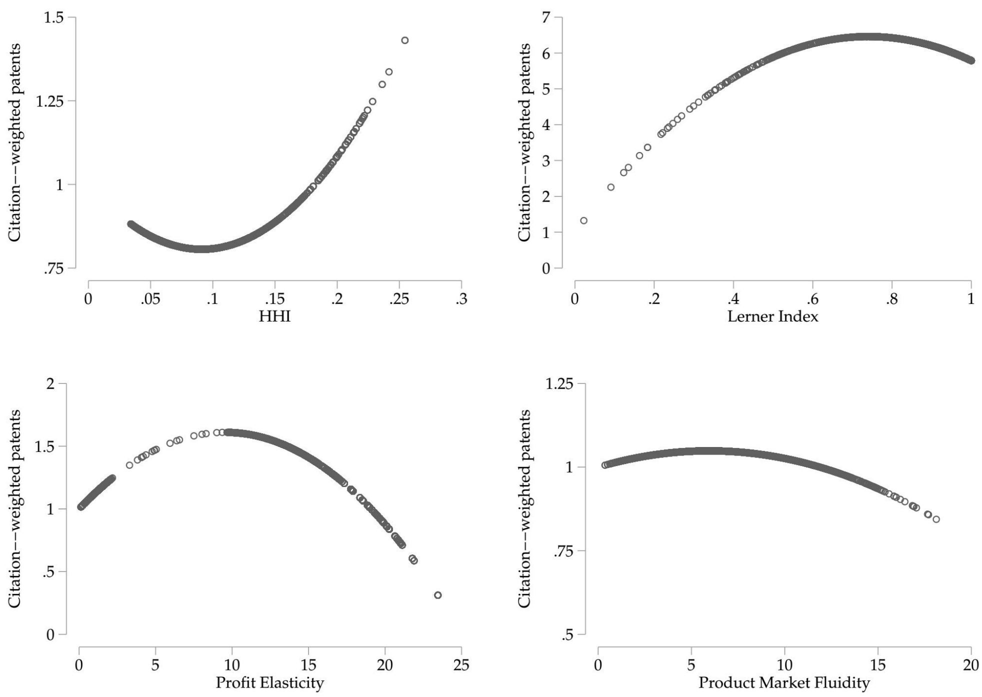
Notes: Coefficients are obtained from zero–inflated negative binomial regression. Estimation is for the subsample of 1975–2001. Inflation variable is a dummy, which takes value of 1 if the number of employees exceeds 500. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2.3 Inverted–U Shape Relationship

We proceed with the discussion of possible non–linear or, more precisely, inverted–U type relationship between competition and innovation. Parametric specification with quadratic term of the independent variable has confirmed the non–linearity in broad terms, however, it is not possible to infer precise shape of the relationship from it. Figure 5.2 provides a graphical representation of the relationship, implied by the coefficients from negative binomial regression of citation–weighted patents on different measures of competition, as in Table 5.5. LI and PE, being the most robust measures throughout different specifications, show a clear non–linear relationship.

In order to verify the evidence from parametric quadratic specification, this study employs a testing procedure, described in Lind & Mehlum (2010), as well as conventional Wald test for joint significance of coefficients β_1 and β_2 in Equation 4.14. Table 5.10 reports t–statistics, p–values and additional parameters of the test applied to negative binomial panel data regression of citation–weighted patents on measures of competition and controls. Sasabuchi test refers to the procedure, optimized by Lind & Mehlum (2010), and has a null hypothesis of monotone or U–shape and alternative hypothesis of inverted–U shape. Simi-

Figure 5.2: Competition and Innovation: Implied Relationship



Notes: Dependent variable is citation–weighted patents. The specification is the same as in Table 5.5 and uses negative binomial panel data regression.

larly to the findings in Table 5.5, both tests strongly reject the null for LI and PE on 1% confidence level, and do not reject it for PMF. Notably, performing the same testing procedures on zero–inflated negative binomial regression yields a rejection of the null for PMF on 1% confidence level. Slope values for lower and upper boundaries of LI and PE are highly significant as well, starting positive and reverting to negative at the extremum points of 0.74 for LI and 9.54 for PMF, which can also be interpreted as the "optimal" values of competition in terms of maximizing innovation. This confirms that at least some measures of innovation exhibit inverted–U shape relationship with measures of competition, and these results are fairly robust across different proxy variables.

We next perform a piecewise regression of innovation measures on proxies for competition, splitting the sample by quartiles of the latter. The results are reported in Table 5.11. We obtain some weak evidence of inverted–U shape, especially for the PE measure, however, the results are not robust throughout different specifications. This might be because of the peculiarities of the data, discussed in the previous subsection. Overall, the evidence of non–linear relationship between competition and innovation appears to be fairly strong,

Table 5.10: Inverted–U Tests: Wald Joint Significance and Sasabuchi Intersection–Union Tests

	(1) LI	(2) PE	(3) PMF
Wald test	209.02	67.22	1.35
p–value	0.00	0.00	0.51
Sasabuchi test	6.43	7.46	0.79
p–value	0.00	0.00	0.22
Interval	[0.02; 1]	[0.12; 32.55]	[0.36; 24.70]
Slope	[14.30; -5.17]	[0.13; -0.31]	[0.02; -0.05]
Extremum	0.74	9.54	5.94
Fieller interval	[0.69; 0.77]	[8.48; 10.74]	[.]

Notes: Wald test has a null of joint insignificance of coefficients β_1 and β_2 as in Equation 4.14. Fieller interval is defined on 95% confidence level.

however, testing over different sectors, geographical regions and levels of disaggregation might be insightful and necessary to reconcile these findings.

Table 5.11: Competition and Innovation: Piecewise Regression by Quartiles of Independent Variable

	25_{th}	50_{th}	75_{th}	100_{th}
R&D				
LI	-0.180	1.146	-0.255	-1.799
	(-0.98)	(1.25)	(-0.20)	(-1.55)
PE	0.549***	0.060**	-0.005	-0.006
	(2.98)	(2.30)	(-0.24)	(-1.37)
PMF	-0.005	0.014	0.025**	0.019***
	(-0.40)	(0.90)	(2.09)	(2.91)
Patents (weight.)				
LI	-0.274	-0.407	5.906	5.131
	(-0.69)	(0.11)	(0.89)	(0.75)
PE	0.149***	0.131	-0.043	-0.014
	(3.60)	(1.61)	(-0.69)	(-1.10)
PMF	0.030	0.030	0.125**	-0.023
	(0.46)	(0.46)	(2.41)	(-0.88)

Chapter 6

Robustness Analysis

6.1 Endogeneity of Competition: Theoretical Perspective

As has been argued earlier, the specification in Equation 4.14 may suffer from endogeneity bias. Concerns, connected with the fact that product market competition is unlikely to be a completely exogenous with respect to innovation, have been voiced by, for example, Aghion *et al.* (2005), who called this issue a “major obstacle to empirical research in this area”. Gilbert (2006) depicts examples from aircraft and steel industry, where increase in innovation led to higher concentration. Polder & Veldhuizen (2012) argue that the studies, which employ micro–level panel data with sufficiently long panels—such as this one—are less prone to suffer from this simultaneity bias. However, in order to obtain a robust evidence on competition–innovation relationship, we address the issue directly.

The problem is well recognized in the literature. The most theoretically robust way to address it is to use “natural experiments”, usually connected with policy changes or import penetration, to introduce a purely exogenous change to the level of competition. For example, Aghion *et al.* (2005) uses a broad range of policy changes, which resulted from the Thatcher era privatizations, the EU Single Market Programme and the Monopoly and Merger Commission actions, to instrument changes in competitive pressure using Two–Stage Least Squares (2SLS) procedure. Similarly, Carlin *et al.* (2004) use the effects of privatizations in transition economies as an instrument. Bos *et al.* (2013) applies this approach to the financial services sector and models an exogenous shock to the level of competition using adoption of Riegle–Neal Act, which deregulated banking industry. Alternatively, some authors use lagged value of independent variable as an instrument in 2SLS specification (see *e.g.* Blundell *et al.* 1999, Bos *et al.* 2013 and Polder & Veldhuizen 2012).

It is clear that, while using different measures of competition as in Section 5.2 provides a good robustness check, it does not *per se* address endogeneity issue since all these measures are of somewhat similar nature. This study thus addresses the problem in other ways. First, we use lagged values of competition variable as an instrument. Following Bos *et al.* (2013), we define lag structure according to the presence of serial autocorrelation in the residuals; Arellano–Bond test is performed to detect it. Blundell *et al.* (1999) argue that this is a theoretically correct way to deal with endogeneity, although it does not account for all possible intertemporal variation.

The second approach owes to Hashmi (2013), who constructs additional instruments for the measures of competition:

1. *Average tariff rate:* defined as the amount of duties, collected by the US government, divided by *fob* (free–on–board) value of imported goods.

2. *Average freight rate:* defined as value of imported goods *cif* (cost, insurance and freight) divided by value of imported goods *fob*, minus 1.

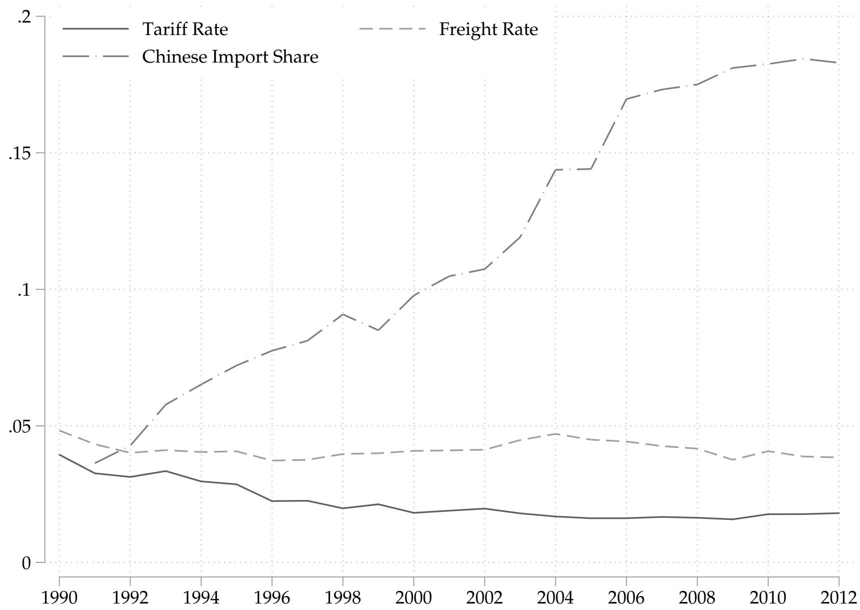
Authors argue that changes in these variables are induces by the state of international agreements and overall cost of transportation, and domestic level of innovation is unlikely to influence them, which is why they can be used as instruments for the level of competition. The data on US imports is due to Schott (2008)[1] and UN Comtrade Database[2].

Finally, we draw upon an original research by Bloom *et al.* (2011), who studied an effect of China's entry to the WTO in 2001 on innovative behavior of firms in twelve European countries. Authors show that this event, accompanied by the abolition of quotas on textiles and clothing export earlier enforced by the Multi–Fiber Agreement, led to a dramatic increase in Chinese exports to the Western countries. Since the cancellation of quotas in 2002 and 2005 was not widely anticipated and can be viewed as an exogenous shock to competition, the value of imports from China as a share of total world imports to the US can be used as an instrument. Figure 6.1 shows a drastic increase in Chinese imports share especially starting from year 2000 without associated decrease in tariff or freight rates.

[1]Available at http://faculty.som.yale.edu/peterschott/sub_international.htm.

[2]Available at http://comtrade.un.org/.

Figure 6.1: Tariff Rates, Freight Rates and Chinese Imports Shares



Source: Schott's International Economics Data, UN Comtrade Database.

6.2 Endogeneity of Competition: Empirical Findings

The following section contains key empirical findings on innovation–competition relationship, modeled by the Instrumental Variable (IV) approach using the instruments, described in Section 6.1. Following *e.g.* Bos *et al.* (2013) and Polder & Veldhuizen (2012), we first assess the validity of lagged values of competition measures as the instruments. When working with patent counts and citations specifications, we are forced to abandon negative binomial model in favor of simple panel data with fixed effects regression, as the testing procedures for autocorrelation and endogeneity are not developed for count data. For this reason patents and citations variables are also log–transformed to obtain comparable scale. The equations are further simplified by omitting interaction term of DTF and competition measure, since it is obviously correlated with the latter and presents additional endogeneity issues.

Table 6.1 presents the results of instrumental variables regression with first to third lag of competition variable as the instruments. It also shows the output of Arellano–Bond test for serial autocorrelation in residuals and Sargan–Hansen test of overidentification for the panel data instrumental variable regression with the lagged values of competition measures as the instruments. The former test has a null hypothesis of the absence of correlation, while for the latter null states that the instruments are valid, that is uncorrelated with the error term. Additionally, the table contains c–statistic and p–values for Durbin–Wu–Hausman test with the null stating that the regressors, which were specified as endogenous, can actually be treated as exogenous. We present only the regression coefficients for the specification with citation–weighted patents, and the remainder of the results, which are qualitatively similar, is presented in Appendix E.

Table 6.1: Instrumental Variables Regression: Citation–Weighted Patents and Lags of Competition Variables

	(1)	(2)	(3)	(4)
HHI	-10.78***			
	(-4.95)			
LI		-2.065***		
		(-2.62)		
PE			0.0518***	
			(2.82)	
PMF				0.0511
				(0.82)
DTF	0.509***	1.034***	0.473***	0.0314
	(3.18)	(4.59)	(3.10)	(0.12)
Spillovers	-0.0184	-0.0108	-0.0108	-0.00266
	(-1.09)	(-0.74)	(-0.55)	(-0.12)
Employment	0.296***	0.292***	0.309***	0.0702
	(6.64)	(6.58)	(6.75)	(0.68)
Debt	-0.230**	-0.149	-0.224*	0.0467
	(-2.05)	(-1.34)	(-1.80)	(0.18)
ROI	0.0692**	0.0464	0.0450	0.254***
	(2.12)	(1.54)	(1.57)	(3.02)
Observations	24821	26862	23480	3368
R^2	0.013	0.009	0.009	0.006
Sargan–Hansen	0.119	1.690	1.407	1.553
p–value	0.942	0.430	0.495	0.460
DWH test	4.019	1.875	4.205	0.135

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Table 6.1 – *Continued from previous page*

	(1)	(2)	(3)	(4)
p–value	0.0450	0.1709	0.0403	0.7131
AB test (1)	-27.60	-28.63	-27.05	-16.66
p–value	0.00	0.00	0.00	0.00
AB test (2)	1.723	1.151	1.570	1.053
p–value	0.0849	0.250	0.116	0.292
AB test (3)	-1.578	-1.367	-1.404	-0.269
p–value	0.115	0.172	0.160	0.788

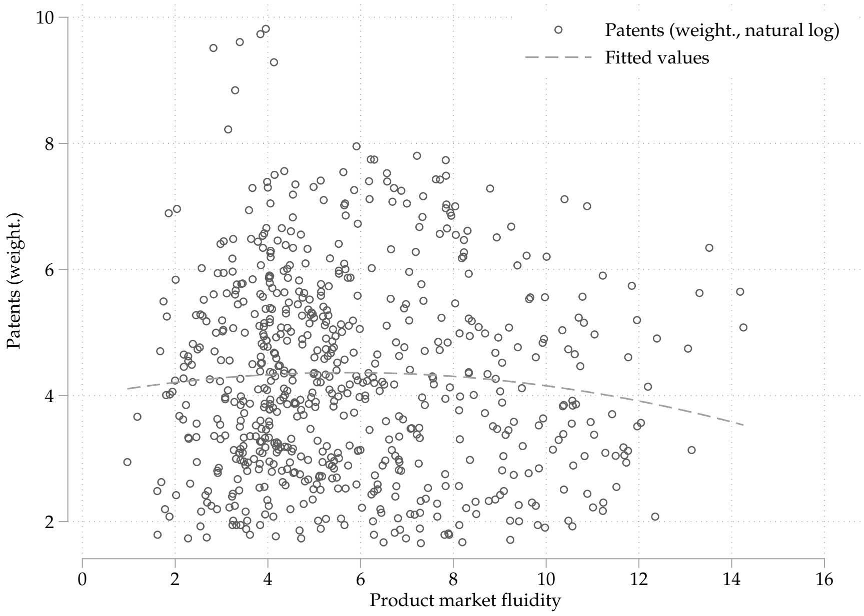
Notes: Dependent variable is citation–weighted patents. Sargan–Hansen test has a null of valid instruments. Durbin–Wu–Hausman test has a null that instrumented variables are exogenous. Arellano–Bond test has a null of absence of serial autocorrelation in residuals. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The regression coefficients mainly remain similar to the specifications in Section 5.2, except for the LI which reverts to negative (interestingly, Hashmi 2013 documents such reversal as well, arguing that endogeneity issues are serious for the dataset of US companies, unlike for the sample of UK companies, used in Aghion *et al.* 2005). According to Sargan–Hansen j–statistic, the instruments bear some credibility, as the null of valid instruments was not rejected. The Durbin–Wu–Hausman test presents some weak evidence on endogeneity of competition variables, however, not in the case of PMF, which in this sense appears to be distinctly different from other competition measures. The hypothesis of the absence of serial autocorrelation for competition measures generally could not be rejected as well according to Arellano–Bond test on first to third lags, which indicates that for the present sample lagged values can in fact be considered as valid instruments.

We nevertheless proceed by testing the same specification using the instrument variables, described in the previous section. Regressions are performed on North American Industry Classification System (NAICS)–4 level, as the nature of instrumental variables does not allow firm–level specifications. Regulated utilities and financial companies are excluded. It is shown on Figure 6.2 that in this specification competition and innovation exhibit roughly similar relationship as for the firm–level regressions: there is a weak resemblance to the inverted–U shape.

Table 6.2 presents the coefficients from the first stage regression of competition measures on instrumental variables. Following Correa & Ornaghi (2014),

Figure 6.2: Citation–Weighted Patents and PMF: Actual and Fitted Values



Source: Compustat, Hoberg–Phillips Data Library, author's calculations.

lagged values are used. F–test has the null of joint insignificance of regression coefficients. When the coefficients are significant, they have expected signs: measure of tariff and freight rates are negatively associated with the degree of competition, while share of Chinese imports—positively. F–test suggests that instruments are fairly strong for HHI and PMF measures, however caution must be exercised when interpreting the results which follow as the test does not satisfy the "rule of thumb", mentioned in Hashmi (2013)—the F–test with the value of test statistic below 10 indicates a problem of weak instruments.

Table 6.2: Instrumental Variables: First Stage Regression

	Tariff Rate (Lag)	Freight Rate (Lag)	China Import Share (Lag)	F–test	Obs.
HHI	-0.0197	0.1163***	-0.0191**	6.79	708
	(-0.62)	(4.14)	(1.99)	[0.0002]	
LI	-0.1174**	0.0545	0.0144	1.88	1107
	(-1.99)	(1.18)	(1.47)	[0.1305]	
PE	4.1023	-12.3112***	2.2187	3.57	897
	(0.46)	(-2.63)	(1.55)	[0.0137]	
PMF	1.3252	1.2816	3.3758***	9.99	849
	(0.60)	(0.52)	(5.32)	[0.0000]	

Table 6.3 shows the results of panel data instrumental variable regression with first lags of tariff rate, freight rate and share of Chinese imports as the instruments for the respective measure of competition. As before, we report outputs of Sargan–Hansen test of overidentification and Durbin–Wu–Hausman endogeneity test. The results for the alternative measures of innovation are shown in Appendix E.

Table 6.3: Instrumental Variables Regression: Citation–Weighted Patents, Tariffs, Freight and Chinese Imports Measures

	(1)	(2)	(3)	(4)
HHI	-91.93			
	(-1.04)			
LI		356.4		
		(1.18)		
PE			1.251*	
			(1.80)	
PMF				4.122*
				(1.73)
DTF	-4.502	-16.53	-10.36*	-10.26
	(-0.93)	(-0.94)	(-1.77)	(-1.57)
Spillovers	-0.240*	-0.271	-0.213	0.134
	(-1.86)	(-0.44)	(-0.87)	(0.55)
Employment	0.157	-1.713	-0.381	-0.847
	(0.16)	(-1.36)	(-0.56)	(-0.90)
Debt	1.166	-16.02	7.740	20.06**
	(0.28)	(-0.77)	(1.52)	(1.98)
ROI	-0.633	26.46	-4.062	0.133
	(-0.37)	(1.21)	(-1.43)	(0.04)
Observations	702	756	642	502
Sargan–Hansen	51.114	2.860	23.935	11.103
p–value	0.00	0.2393	0.00	0.0039
DWH test	2.583	45.978	10.919	3.864
p–value	0.1080	0.00	0.0010	0.0493

Notes: Dependent variable is citation–weighted patents. Sargan–Hansen test has a null of valid instruments. Durbin–Wu–Hausman test has a null that instrumented variables are exogenous. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The table shows that main independent variables—the measures of competition—are fairly robust to controlling for endogeneity: all of them have expected signs, similar to those in Section 5.2, and coefficients for PE and PMF are significant on 10% level. It should be noted however that Sargan–Hansen test does not confirm the validity of instruments, even despite the fact that, as explained by Hashmi (2013), they have some *ex ante* credibility as the argument in favor of their exogeneity is quite compelling. These results suggest that the relationship between competition and innovation might be better modeled by complex 3SLS setups such as in Peneder & Woerter (2013). Overall, however, we conclude that, in line with findings above, competition has a positive effect on innovation, but endogeneity of competition measure is in fact a serious issue, which should be properly addressed with IV technique.

Chapter 7

Conclusion

This study investigates the relationship between competition and innovative performance in the dataset of publicly traded US companies over the period of 1975–2013. We consider predictions of the so–called Schumpeterian hypothesis and endogenous growth model by Aghion *et al.* (1998) that firms in less competitive environment innovate more; on the other hand, agency models by *e.g.* Hart (1983), "replacement effect" from Arrow (1962) and "escape competition effect", as formulated in Aghion *et al.* (1999), offer an opposite prediction. The objective of this thesis is to reconcile existing theoretical and empirical evidence by drawing upon seminal research by Aghion *et al.* (2005) and testing for the non–linear association between the two variables, known as the inverted–U shape relationship.

Similarly to the new empirical studies by Hashmi (2013) and Correa & Ornaghi (2014), we document positive and significant relationship between innovation, as measured by R&D expenditures, patent counts and citation–weighted patents, and the level of competition when controlling for size, firm and industry fixed–effects and other firm–specific characteristics. Additionally, following studies by *e.g.* Aghion *et al.* (2005) and Nieto & Quevedo (2005), we show that firm's innovative performance is generally positively associated with the DTF and the level of technological opportunities, and negatively—with the amount of knowledge spillovers, although these results are not robust across all the specifications.

We obtain fresh insights on the association between competition and innovation by employing two novel measures of the former: the PE, developed by Boone (2008), and the PMF, designed by Hoberg *et al.* (2014). As discussed in Section 4.2, these measures are clearly distinct from traditionally used HHI and

LI, and the similarity of findings across all the four measures confirms the robustness of the results. In addition, we use graphical exploratory analysis, parametric specifications with quadratic terms, piecewise regressions by quartiles of competition variable and the modified version of so–called intersection–union test, developed by Lind & Mehlum (2010), to document contrary to Hashmi (2013) a strong evidence of the inverted–U shape relationship between competition and innovation, which holds across different measures of these variables.

The relationship also appears to be fairly robust to the changes in specification from firm–level to industry–level regression, as initially done by Aghion *et al.* (2005), subsampling by time–periods and using different proxies for depended and independent variables. In addition, following the most recent studies in the area of industrial organization, we improve upon the methodology in Aghion *et al.* (2005) by using negative binomial panel data regression to account for apparent overdispersion in our count data variables (such as number of patents and citations obtained by firm), as well as its modification, known as zero–inflated negative binomial regression, in order to correct for the prevalence of zero observations of patent counts and citations in the data. Finally, in order to directly address the issue of apparent endogeneity of competition measure and perform additional test of robustness, we draw upon the methodology in Bloom *et al.* (2011) and Hashmi (2013) and construct several instrumental variables based on lagged values of competition, import tariff rates and the level of Chinese imports penetration. The panel data instrumental variables regressions overall document a weak evidence of positive relationship between competition and innovation, confirming previous findings.

The findings discussed above have important policy implications. As noted by Gilbert (2006), enforcement actions of US and European antitrust authorities often assume an adverse effect of increased concentration on the incentives to innovate. The growing body of empirical literature which documents a non–monotonic relationship between competition and innovation—including this study—suggests that this is not always true, and that regulatory actions should be undertaken according to the pre–event (should it be merger, technological alliance or foreign direct investments) level of concentration and "neck–to–neckness" in the sector (that is, the degree of variation in technological level of firms).

In our view, this work suggests at least three possible areas of future research. First, recent findings in international economics literature, as well as natural language processing approach in Hoberg *et al.* (2014), represent evolution in modeling abstract concept of competition, and further inquiry into this subject will likely provide new insights. Second, it is necessary to further research the proper ways of dealing with micro–level, highly overdispersed panel data. Apart from models which account for zero–inflation, another approach is suggested by Berube *et al.* (2012) and involves estimation of Heckman two–stage selection model to correct for observations with missing innovation output; the true functional form of the selection equation is however unclear. Finally, findings in Chapter 6 clearly indicate that endogeneity is in fact a serious issue when modeling competition–innovation relationship; this dictates the necessity to appeal to more complex definitions of innovation process. A prominent attempt of this has been performed by Peneder & Woerter (2013) who tie together level of competition, innovative effort and outcome of innovative activity into a system of three simultaneous equations.

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Appendix A

Pavitt Classification

Table A.1: Pavitt Industry Classification

Pavitt taxonomy	NAICS code	Description
Resource–intensive	311	Food Manufacturing
	312	Beverage and Tobacco Manufacturing
	321	Wood Manufacturing
	322	Paper Manufacturing
	324	Petroleum and Coal Product Manufacturing
	327	Non–Metallic Mineral Product Manufacturing
Labor–intensive	313	Textile Mills
	314	Textile Product Mills
	315	Clothing Manufacturing
	316	Leather and Allied Product Manufacturing
	332	Fabricated Metal Product Manufacturing
	337	Furniture and Related Product Manufacturing
	339	Miscellaneous Manufacturing
Scale–intensive	323	Printing and Related Support Activities
	325	Chemical Manufacturing
	331	Primary Metal Manufacturing
	3361–3363, 3365, 3366, 3369	Transportation Equipment Manufacturing
Science–Based	334	Computer and Electronic Product Manufacturing
	3364	Aerospace Product and Parts Manufacturing
Specialized	333	Machinery Manufacturing
	335	Electrical Equipment Manufacturing

Source: Pavitt (1984), Berube *et al.* (2012).

Appendix B

Summary Statistics

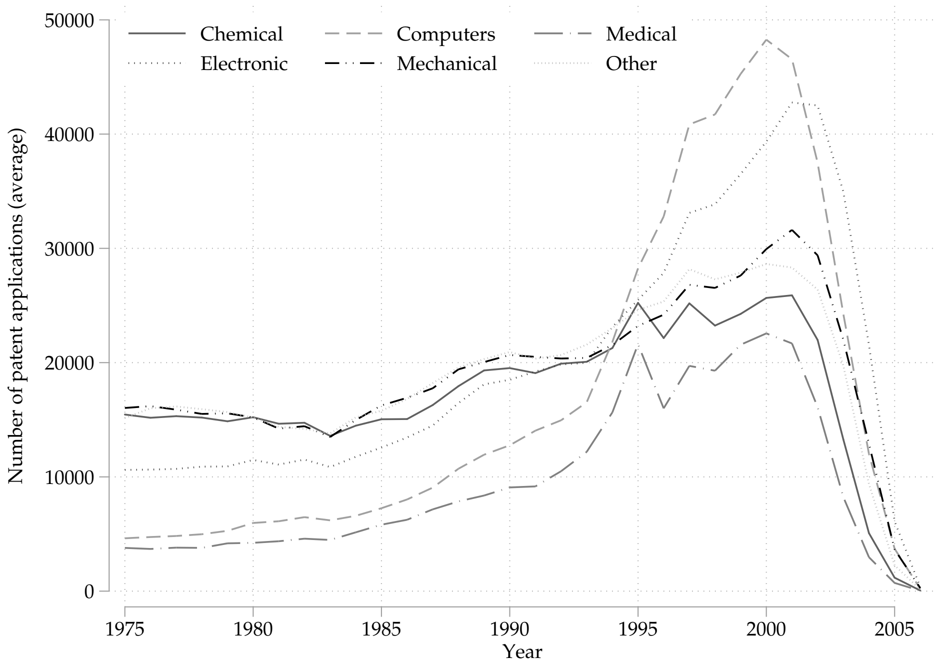
Table B.1: Summary Statistics: 1990–2001

Variable	*Mean*	*Std. Dev.*	*Min.*	*Max.*	*N*
R&D Expenditures	1.46	1.81	0	9.32	46238
Number of Patents	14.8	76.52	0	2505	35882
Number of Citations (5–year)	47.6	312.97	0	10231	32734
Citation–Weighted Patents	225.5	1305.85	0	43336.11	35882
HHI	7.57	0.79	5.53	9.21	8330
LI	0.92	0.06	0.23	1	46238
PE	7.45	2.61	0.07	26.67	38094
PMF	5.23	2.57	0.36	18.32	6567
DTF	0.18	0.09	0	0.84	20596
Spillovers	5.65	3.38	-8.88	11.51	46238
Number of Employees	7.18	1.96	0	13.66	46238
Debt–to–Equity	1.78	84.19	0	15335	46138
ROI	0.21	0.37	0	69.88	46067

Table B.2: Summary Statistics: 2002–2013

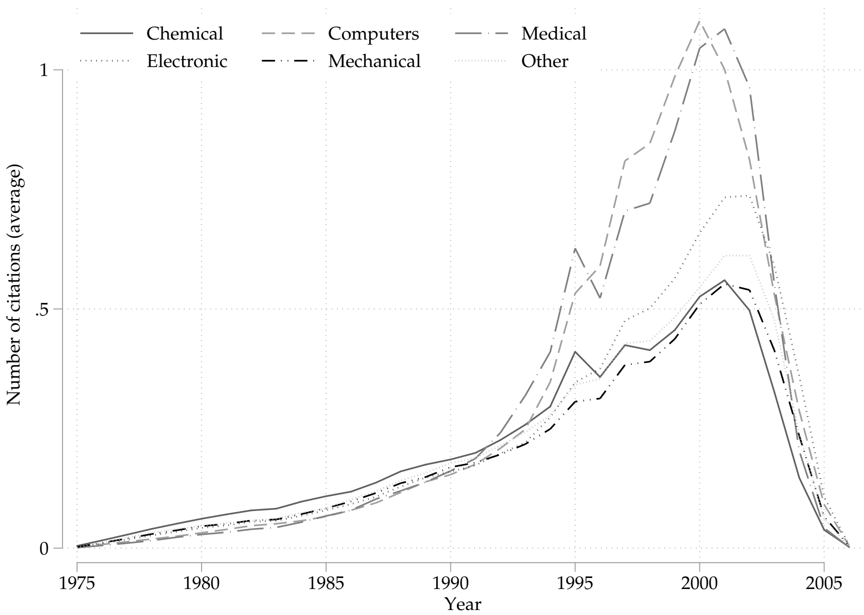
Variable	*Mean*	*Std. Dev.*	*Min.*	*Max.*	*N*
R&D Expenditures	1.49	1.98	0	9.55	52984
HHI	0.06	0.02	0.03	0.22	17226
LI	0.95	0.08	0.08	1	52984
PE	5.49	3.22	0.02	33.32	45619
PMF	6.82	3.67	0	27.59	34908
DTF	0.27	0.22	0	1	52984
Spillovers	6.78	4.37	-9.48	12.29	52984
Number of Employees	6.86	2.36	0	14.6	52984
Debt–to–Equity	0.19	0.19	0	0.95	52984
ROI	-0.03	0.52	-3.85	0.81	52984

Figure B.1: Average Number of Patent Applications, per Technological Category



Source: NBER Database, author's calculations.

Figure B.2: Average Number of Citations Received by Patent, per Technological Category



Source: NBER Database, author's calculations.

Table B.3: Product Market Fluidity: Manufacturing

SIC Industry	Product Market Fluidity 1997–2002	2003–2008	2009–2013
Food and Kindred (20)	3.94	4.11	4.42
Tobacco (21)	8.61	7.20	6.12
Textile (22)	3.61	3.29	3.49
Apparel (23)	3.87	4.07	4.15
Lumber and Wood (24)	4.17	4.31	4.18
Furniture (25)	3.48	3.70	3.65
Paper (26)	3.58	3.47	3.66
Printing and Publishing (27)	4.60	4.34	5.00
Chemicals (28)	6.28	7.49	8.34
Petroleum Refining (29)	6.05	6.39	7.97
Rubber and Plastic (30)	4.25	3.88	3.69
Leather (31)	4.07	4.30	4.10
Stone, Clay, Glass, Concrete (32)	4.67	5.11	5.56
Primary Metal (33)	4.95	4.68	4.29
Fabricated Metal (34)	3.76	4.07	4.12
Machinery and Equipment (35)	5.43	5.29	5.12
Electronics and Equipment (36)	6.14	6.07	5.64
Transportation Equipment (37)	4.31	4.54	4.43
Instruments, Optics, Watches (38)	6.31	7.08	7.32
Miscellaneous Manufacturing (39)	4.59	4.88	4.64

Table B.4: Profit Elasticity: Manufacturing

SIC Industry	Profit Elasticity			
	1975–1985	1986–1995	1996–2005	2005–2014
Food and Kindred (20)	7.66	8.53	8.17	8.78
Textile (22)	12.06	8.69	7.41	–
Apparel (23)	8.76	11.37	10.93	7.37
Lumber and Wood (24)	9.50	7.82	7.84	7.53
Furniture (25)	8.27	11.73	9.17	12.47
Paper (26)	6.34	6.79	7.27	6.99
Printing and Publishing (27)	5.17	5.98	5.41	5.31
Chemicals (28)	6.54	6.91	6.53	5.18
Petroleum Refining (29)	2.29	3.83	3.22	3.61
Rubber and Plastic (30)	6.25	5.24	7.65	6.13
Leather (31)	7.20	12.86	15.78	15.50
Stone, Clay, Glass, Concrete (32)	6.53	6.36	5.51	–
Primary Metal (33)	6.08	6.82	6.95	6.29
Fabricated Metal (34)	5.25	8.19	9.70	6.70
Machinery and Equipment (35)	5.93	6.99	7.48	7.19
Electronics and Equipment (36)	6.05	6.98	7.52	7.31
Transportation Equipment (37)	6.18	7.29	6.36	6.63
Instruments, Optics, Watches (38)	4.89	5.85	4.84	5.93
Miscellaneous Manufacturing (39)	6.08	6.76	4.46	7.72

Appendix C

Variables Construction

Table C.1: Variables Construction

Variable	*Period*	*Construction*
1. Competition Measures		
Lerner Index	1975—2013	Following Aghion *et al.* (2005), calculated as 1 minus the difference between operating profit (Compustat item *oiadp*) and financial cost (gross PP&E—item *ppegt*—multiplied by the cost of capital, assumed to be equal 0.085), divided by sales (item *sale*).
HHI	1996—2013	The measure is based on Hoberg & Phillips (2010) is obtained from Hoberg–Phillips Data Library.

Continued on next page

Table C.1 – *Continued from previous page*

Variable	*Period*	*Construction*
Fluidity	1996—2013	The measure is based on Hoberg *et al.* (2014) is obtained from Hoberg–Phillips Data Library.
Boone Indicator (PE)	1975—2013	According to Equation 4.6, measure of profitability (LI) is regressed on natural log of average variable costs (defined as operating expenses—item *xopr*—divided by sales) and natural log of firm's employment (item *emp*), sorting by industry and year; industry–year observations with less than 10 firms are excluded. The resulting estimates of $-\hat{\beta}_{it}$, or the coefficient for average variable costs, is used as a PE measure.
2. Innovation Measures		
R&D	1975—2013	Natural logarithm of real R&D expenses (item *xrd*) plus 1.
Raw Patent Counts	1975—2006	Number of patents, acquired by firm (uniquely identified by *gvkey*) in a current year.
Citation–Weighted Patents	1975—2006	Number of patents, acquired by firm in a current year, multiplied by the number of citations, received by the corresponding patents in their lifetime, adjusted for truncation as in Hall *et al.* (2001).
Citation Index	1975—2006	Number of citations for the patents, acquired by firm in the most recent five–year period.
3. Control Variables		

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Table C.1 – *Continued from previous page*

Variable	*Period*	*Construction*
DTF	1990—2013	According to Equation 4.12, TFP is calculated as real sales divided by cost of labor (defined as an average annual wage in manufacturing multiplied by number of employees), cost of intermediate inputs (defined as total operating expenses minus cost of labor) and cost capital (defined as real gross PP&E multiplied by 0.085). TFP of a leading firm is defined as 95^{th} percentile of the TFP in a respective SIC–2 industry and year. DTF is then defined according to Equation 4.11.
Knowledge Spillovers	1975—2013	Calculated according to Equation 4.13, with the sector defined by SIC–3 industry. Inverse hyperbolic sine transformation is applied to this number.
Tech. Opportunity	1975—2013	Calculated according to Pavitt (1984) and Berube *et al.* (2012); the split is presented in Table A.1.
Employment	1975—2013	Natural log of number of employees; serves either as a proxy for market structure, or as a control for firm's size in different specifications.
Debt–to–Equity	1975—2013	Sum of long–term (item *dltt*) and short–term debt (item *dlc*) divided by common equity (item *ceq*).
Return on Investment	1975—2013	Earnings before interest and taxes (item *ebit*) divided by invested capital (item *icapt*). Due to presence of extreme values we preform light winsorization of the data (0.5% in each tail).

Appendix D

Alternative Specifications and Robustness Analysis

Table D.1: Competition and Innovation: Patent Count

	(1)	(2)	(3)	(4)
HHI	-10.77***			
	(-4.87)			
HHI^2	38.42***			
	(3.71)			
LI		2.527		
		(1.24)		
LI^2		-1.638		
		(-1.37)		
PE			0.0519***	
			(3.81)	
PE^2			-0.00236***	
			(-3.33)	
PMF				-0.00532
				(-0.30)
PMF^2				0.000225
				(0.25)
DTF	0.967***	-6.040***	0.428***	-0.234
	(4.41)	(-3.39)	(2.88)	(-0.94)
Spillovers	-0.00506	-0.00251	0.00148	0.0147**

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Table D.1 – *Continued from previous page*

	(1)	(2)	(3)	(4)
	(-1.18)	(-0.65)	(0.30)	(2.00)
Employment	0.150***	0.126***	0.123***	0.128***
	(18.37)	(16.16)	(15.51)	(7.66)
Debt	0.108*	0.0924	0.0874	0.147
	(1.71)	(1.48)	(1.34)	(1.40)
ROI	0.0154	0.0205	0.0232	0.0922**
	(0.59)	(0.79)	(0.88)	(2.30)
$DTF * Comp$	-12.83***	6.439***	-0.0110	0.0383*
	(-2.99)	(3.59)	(-0.41)	(1.73)
Constant	-0.321***	-1.569*	-0.928***	0.242
	(-2.73)	(-1.83)	(-8.82)	(1.30)
Observations	25095	26744	24108	8928

Notes: Dependent variable is patent count. Coefficients are obtained from negative binomial panel data regression. Estimation is for the subsample of 1975–2001. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.2: Competition and Innovation: Citation Index

	(1)	(2)	(3)	(4)
HHI	-14.10***			
	(-7.55)			
HHI^2	51.21***			
	(6.07)			
LI		5.032***		
		(2.66)		
LI^2		-2.775**		
		(-2.50)		
PE			0.0901***	
			(6.71)	
PE^2			-0.00448***	
			(-6.22)	
PMF				0.0163
				(1.09)
PMF^2				-0.00105

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Table D.2 – *Continued from previous page*

	(1)	(2)	(3)	(4)
				(-1.33)
DTF	0.346*	-10.05***	0.302**	0.195
	(1.83)	(-6.05)	(2.28)	(0.96)
Spillovers	0.00396	0.00949***	0.0115**	0.0159**
	(1.00)	(2.67)	(2.53)	(2.55)
Employment	0.219***	0.198***	0.194***	0.255***
	(31.81)	(30.50)	(29.15)	(19.47)
Debt	0.0573	-0.0581	0.0299	-0.138
	(0.99)	(-1.01)	(0.50)	(-1.54)
ROI	-0.0610***	-0.0435**	-0.0429**	0.0210
	(-3.03)	(-2.12)	(-2.08)	(0.74)
$DTF * Comp$	0.572	10.34***	0.0224	0.00936
	(0.15)	(6.18)	(0.93)	(0.50)
Constant	-1.406***	-4.100***	-2.301***	-1.261***
	(-14.10)	(-5.14)	(-24.32)	(-8.58)
Observations	23995	25486	22968	8830

Notes: Dependent variable is CI. Coefficients are obtained from negative binomial panel data regression. Estimation is for the subsample of 1975–2001. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.3: Competition and Innovation: Patent Count (Zero–Inflated Negative Binomial Regression)

	(1)	(2)	(3)	(4)
HHI	-25.78***			
	(-4.32)			
HHI^2	90.49***			
	(3.08)			
LI		3.934		
		(0.54)		
LI^2		-5.460		
		(-1.28)		
PE			0.188***	
			(4.28)	

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Table D.3 – *Continued from previous page*

	(1)	(2)	(3)	(4)
PE^2			-0.0164***	
			(-7.96)	
PMF				0.199***
				(4.84)
PMF^2				-0.00618**
				(-2.41)
DTF	0.758	-19.37***	1.676***	1.448***
	(1.47)	(-2.86)	(5.04)	(3.01)
$Spillovers$	0.114***	0.105***	0.114***	0.106***
	(8.14)	(8.66)	(7.06)	(7.94)
$Employment$	0.902***	0.910***	0.886***	0.883***
	(42.76)	(46.79)	(42.86)	(33.54)
$Debt$	-1.859***	-1.590***	-1.897***	-1.376***
	(-10.07)	(-7.30)	(-10.33)	(-6.46)
ROI	0.162***	0.180***	0.204***	0.249***
	(3.32)	(3.87)	(4.07)	(3.60)
$DTF * Comp$	31.22***	22.76***	0.138**	0.0250
	(2.80)	(3.35)	(2.24)	(0.58)
Constant	-5.255***	-5.351*	-6.732***	-6.665***
	(-18.84)	(-1.76)	(-25.19)	(-22.91)
Inflate:				
$Emp.dummy$	16.86***	16.23	17.12	16.85
	(24.47)	(.)	(.)	(.)
Constant	-19.20***	-18.42	-19.46	-18.78
	(-30.20)	(.)	(.)	(.)
$Alpha$				
Constant	1.396***	1.398***	1.412***	1.309***
	(39.80)	(40.94)	(41.28)	(33.08)
Observations	36827	39812	35867	14326

Notes: Dependent variable is patent count. Coefficients are obtained from zero–inflated negative binomial regression. Estimation is for the subsample of 1975–2001. Inflation variable is a dummy, which takes value of 1 if the number of employees exceeds 500. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.4: Competition and Innovation: Citation-Weighted Patents (Zero–Inflated Negative Binomial Regression)

	(1)	(2)	(3)	(4)
HHI	-43.99***			
	(-5.51)			
HHI^2	157.0***			
	(4.01)			
LI		-7.136		
		(-1.03)		
LI^2		1.198		
		(0.29)		
PE			0.0861	
			(1.51)	
PE^2			-0.0126***	
			(-5.40)	
PMF				0.459***
				(9.81)
PMF^2				-0.0183***
				(-7.04)
DTF	0.0977	-14.01***	0.586	1.941***
	(0.17)	(-2.58)	(1.49)	(3.61)
Spillovers	0.0717***	0.0835***	0.0767***	0.0630***
	(4.11)	(5.54)	(4.12)	(3.71)
Employment	0.714***	0.716***	0.683***	0.742***
	(31.33)	(31.82)	(29.25)	(20.73)
Debt	-1.967***	-1.831***	-2.012***	-1.561***
	(-9.21)	(-7.89)	(-8.82)	(-5.18)
ROI	-0.0407	-0.0804	-0.0205	0.00772
	(-0.67)	(-1.29)	(-0.36)	(0.10)
$DTF * Comp$	25.77**	16.39***	0.140*	-0.129***
	(2.16)	(3.03)	(1.90)	(-2.83)
Constant	1.311***	4.751	-0.444	-2.423***
	(3.83)	(1.62)	(-1.22)	(-5.89)
Inflate:				
Emp.dummy	-0.475***	-0.452***	-0.446***	-0.315***
	(-14.67)	(-14.35)	(-13.52)	(-8.34)

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Table D.4 – *Continued from previous page*

	(1)	(2)	(3)	(4)
Constant	0.339***	0.341***	0.322***	0.239***
	(13.71)	(13.33)	(12.31)	(7.67)
Alpha				
Constant	1.051***	1.092***	1.094***	0.944***
	(21.92)	(21.64)	(20.92)	(14.71)
Observations	36827	39812	35867	14326

Notes: Dependent variable is citation–weighted patents. Coefficients are obtained from zero–inflated negative binomial regression. Estimation is for the subsample of 1975–2001. Inflation variable is a dummy, which takes value of 1 if the number of employees exceeds 500. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.5: Competition and Innovation: Citation Index (Zero–Inflated Negative Binomial Regression)

	(1)	(2)	(3)	(4)
HHI	-42.21***			
	(-5.12)			
HHI^2	158.0***			
	(3.64)			
LI		-2.915		
		(-0.45)		
LI^2		-1.565		
		(-0.42)		
PE			0.108**	
			(2.00)	
PE^2			-0.0134***	
			(-5.90)	
PMF				0.457***
				(10.51)
PMF^2				-0.0173***
				(-6.92)
DTF	0.247	-19.17***	0.836**	2.100***
	(0.41)	(-3.76)	(1.97)	(3.90)
Spillovers	0.0903***	0.0966***	0.0916***	0.0809***

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Table D.5 – *Continued from previous page*

	(1)	(2)	(3)	(4)
	(5.31)	(7.13)	(5.20)	(5.13)
Employment	0.817***	0.818***	0.790***	0.843***
	(36.32)	(40.64)	(36.43)	(30.83)
Debt	-1.809***	-1.669***	-1.821***	-1.359***
	(-9.08)	(-8.01)	(-9.12)	(-5.65)
ROI	-0.187***	-0.174***	-0.150**	-0.134*
	(-2.69)	(-2.69)	(-2.04)	(-1.78)
$DTF * Comp$	30.22**	22.09***	0.167**	-0.0837*
	(2.44)	(4.32)	(2.14)	(-1.73)
Constant	-2.509***	-0.409	-4.280***	-5.572***
	(-7.06)	(-0.15)	(-13.59)	(-17.92)
Inflate:				
Emp.dummy	3.368***	3.680***	4.172***	5.025*
	(3.26)	(3.53)	(26.78)	(1.75)
Constant	-5.846***	-6.166***	-6.470	-6.600**
	(-232.73)	(-326.06)	(.)	(-2.22)
Alpha				
Constant	1.558***	1.573***	1.574***	1.373***
	(49.93)	(52.45)	(50.93)	(38.79)
Observations	29179	31227	28143	11509

Notes: Dependent variable is CI. Coefficients are obtained from zero–inflated negative binomial regression. Estimation is for the subsample of 1975–2001. Inflation variable is a dummy, which takes value of 1 if the number of employees exceeds 500. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix E

Instrumental Variables: Alternative Specifications

Table E.1: Instrumental Variables Regression: R&D and Lags of Competition Variables

	(1)	(2)	(3)	(4)
HHI	-3.347***			
	(-3.63)			
LI		-1.318***		
		(-6.22)		
PE			-0.00946*	
			(-1.75)	
PMF				0.0177
				(1.21)
DTF	0.387***	0.663***	0.332***	0.296***
	(7.87)	(10.03)	(6.77)	(5.76)
Spillovers	-0.0243**	-0.0340***	0.00294	-0.0411***
	(-2.16)	(-3.95)	(0.26)	(-4.95)
Employment	0.371***	0.378***	0.410***	0.397***
	(22.37)	(25.95)	(25.84)	(19.91)
Debt	-0.0653*	-0.0328	-0.0933***	-0.0698
	(-1.86)	(-0.96)	(-2.70)	(-1.62)
ROI	-0.0602***	-0.0681***	-0.0610***	-0.0307*
	(-4.87)	(-6.59)	(-6.05)	(-1.86)
Observations	49970	79796	67532	32239

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Table E.1 – *Continued from previous page*

	(1)	(2)	(3)	(4)
R^2	0.128	0.132	0.154	0.150
Sargan–Hansen	7.328	11.31	2.034	3.848
p–value	0.0256	0.00350	0.362	0.146
DWH test	0.280	4.718	2.016	1.319
p–value	0.5969	0.0298	0.1556	0.2507
AB test (1)	-9.763	-14.55	-10.88	-9.238
p–value	0.00	0.00	0.00	0.00
AB test (2)	-3.583	-7.457	-4.956	-2.176
p–value	0.000339	0.00	0.00	0.0296
AB test (3)	-1.372	-2.580	-1.390	-5.343
p–value	0.170	0.00988	0.164	0.00

Notes: Dependent variable is R&D expenditures. Sargan–Hansen test has a null of valid instruments. Durbin–Wu–Hausman test has a null that instrumented variables are exogenous. Arellano–Bond test has a null of absence of serial autocorrelation in residuals. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.2: Instrumental Variables Regression: Patent Count and Lags of Competition Variables

	(1)	(2)	(3)	(4)
HHI	-6.763***			
	(-4.72)			
LI		-1.281**		
		(-2.33)		
PE			0.0150*	
			(1.84)	
PMF				0.00642
				(0.26)
DTF	0.122*	0.464***	0.130**	0.0459
	(1.83)	(3.50)	(2.00)	(0.44)
Spillovers	0.0143	0.0123	0.0187	-0.00877
	(1.42)	(1.47)	(1.61)	(-1.01)
Employment	0.236***	0.232***	0.244***	0.0566
	(10.97)	(10.84)	(10.68)	(1.36)

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Table E.2 – *Continued from previous page*

	(1)	(2)	(3)	(4)
Debt	-0.0553	-0.0162	-0.0888	0.0416
	(-1.03)	(-0.26)	(-1.41)	(0.41)
ROI	-0.0150	-0.0259*	-0.0225*	0.0263
	(-1.17)	(-1.65)	(-1.90)	(0.88)
Observations	24821	26862	23480	3368
R^2	0.037	0.028	0.036	0.001
Sargan–Hansen	6.812	4.434	3.181	1.063
p–value	0.0332	0.109	0.204	0.588
DWH test	0.827	0.293	1.170	0.029
p–value	0.3631	0.5881	0.2793	0.8657
AB test (1)	-26.12	-27.46	-25.43	-16.48
p–value	0.00	0.00	0.00	0.00
AB test (2)	2.243	1.851	1.828	0.558
p–value	0.0249	0.0641	0.0675	0.577
AB test (3)	-1.747	-1.829	-1.861	1.599
p–value	0.0807	0.0674	0.0628	0.110

Notes: Dependent variable is patent count. Sargan–Hansen test has a null of valid instruments. Durbin–Wu–Hausman test has a null that instrumented variables are exogenous. Arellano–Bond test has a null of absence of serial autocorrelation in residuals. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.3: Instrumental Variables Regression: CI and Lags of Competition Variables

	(1)	(2)	(3)	(4)
HHI	-15.28***			
	(-4.72)			
LI		0.310		
		(0.41)		
PE			0.00517	
			(0.36)	
PMF				0.0166
				(0.47)
DTF	0.367**	0.283	0.373***	0.0761

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Table E.3 – *Continued from previous page*

	(1)	(2)	(3)	(4)
	(2.34)	(1.17)	(2.75)	(0.48)
Spillovers	0.0730***	0.0702***	0.0939***	-0.00117
	(5.88)	(6.51)	(5.55)	(-0.11)
Employment	0.460***	0.445***	0.460***	0.116*
	(10.79)	(10.61)	(10.52)	(1.90)
Debt	0.126	0.0444	0.0511	-0.282*
	(1.11)	(0.37)	(0.46)	(-1.75)
ROI	-0.0730**	-0.0790**	-0.0743**	-0.00528
	(-2.12)	(-2.24)	(-2.27)	(-0.09)
Observations	20897	22480	19698	2880
R^2	0.076	0.069	0.076	-0.001
Sargan–Hansen	9.449	3.264	5.582	0.712
p–value	0.00888	0.196	0.0614	0.701
DWH test	0.197	0.180	0.121	0.362
p–value	0.6571	0.6715	0.7275	0.5474
AB test (1)	-13.84	-14.80	-13.04	-8.411
p–value	0.00	0.00	0.00	40.00
AB test (2)	4.465	4.047	4.684	1.417
p–value	0.00	0.00	0.00	0.157
AB test (3)	-4.036	-3.483	-3.829	-3.157
p–value	0.00	0.00	0.00	0.00160

Notes: Dependent variable is CI. Sargan–Hansen test has a null of valid instruments. Durbin–Wu–Hausman test has a null that instrumented variables are exogenous. Arellano–Bond test has a null of absence of serial autocorrelation in residuals. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.4: Instrumental Variables Regression: R&D, Tariffs, Freight and Chinese Imports Measures

	(1)	(2)	(3)	(4)
HHI	8.242			
	(0.66)			
LI		-44.90		
		(-0.82)		

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Table E.4 – *Continued from previous page*

	(1)	(2)	(3)	(4)
PE			0.112*	
			(1.89)	
PMF				-0.123
				(-0.83)
DTF	1.194***	1.411	-0.503	0.290
	(2.73)	(0.60)	(-0.60)	(0.69)
Spillovers	0.0470	-0.0680	0.0602	0.00727
	(1.42)	(-0.51)	(1.63)	(0.36)
Employment	0.656***	0.677***	0.692***	0.679***
	(5.97)	(4.15)	(10.04)	(10.21)
Debt	-1.259**	1.227	-2.112***	-1.515***
	(-2.08)	(0.32)	(-3.97)	(-3.26)
ROI	-0.303	-3.724	-0.967***	-0.265
	(-1.32)	(-1.00)	(-2.72)	(-1.34)
Observations	708	1107	897	849
Sargan–Hansen	15.801	0.827	19.002	7.023
p–value	0.0004	0.6612	0.0001	0.0299
DWH test	0.001	24.987	5.833	3.781
p–value	0.9801	0.00	0.0157	0.0518

Notes: Dependent variable is R&D expenditures. Sargan–Hansen test has a null of valid instruments. Durbin–Wu–Hausman test has a null that instrumented variables are exogenous. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.5: Instrumental Variables Regression: Patent Count, Tariffs, Freight and Chinese Imports Measures

	(1)	(2)	(3)	(4)
HHI	-50.69			
	(-1.39)			
LI		117.8		
		(1.09)		
PE			-0.678	
			(-1.62)	
PMF				1.566

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Table E.5 – *Continued from previous page*

	(1)	(2)	(3)	(4)
				(1.32)
DTF	-1.927	-6.589	-5.048	-5.398*
	(-0.96)	(-0.99)	(-1.50)	(-1.65)
Spillovers	-0.0322	-0.0362	-0.0240	0.0879
	(-0.58)	(-0.17)	(-0.18)	(0.95)
Employment	0.657	-0.252	0.323	-0.115
	(1.53)	(-0.53)	(0.82)	(-0.30)
Debt	-0.0531	-4.416	3.802	8.928*
	(-0.03)	(-0.61)	(1.60)	(1.83)
ROI	-1.374*	7.935	-2.977*	-0.507
	(-1.90)	(1.00)	(-1.80)	(-0.33)
Observations	702	756	642	502
Sargan–Hansen	25.321	4.408	6.523	12.037
p–value	0.00	0.1103	0.0383	0.0024
DWH test	0.754	12.955	16.863	0.682
p–value	0.3851	0.0003	0.00	0.4088

Notes: Dependent variable is patent count. Sargan–Hansen test has a null of valid instruments. Durbin–Wu–Hausman test has a null that instrumented variables are exogenous. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.6: Instrumental Variables Regression: CI, Tariffs, Freight and Chinese Imports Measures

	(1)	(2)	(3)	(4)
HHI	-50.74			
	(-1.09)			
LI		123.8		
		(1.05)		
PE			-0.703**	
			(-2.21)	
PMF				2.201
				(1.24)
DTF	-3.294	-8.738	-7.322*	-8.599**
	(-1.34)	(-1.15)	(-1.93)	(-2.02)

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Table E.6 – *Continued from previous page*

	(1)	(2)	(3)	(4)
Spillovers	0.0235	0.00808	-0.0366	0.0484
	(0.33)	(0.04)	(-0.19)	(0.39)
Employment	0.731	-0.283	0.307	-0.318
	(1.60)	(-0.48)	(0.67)	(-0.57)
Debt	0.562	-3.768	7.023**	12.25*
	(0.29)	(-0.48)	(2.15)	(1.78)
ROI	-2.096**	7.620	-3.818***	-0.978
	(-2.47)	(0.87)	(-2.75)	(-0.50)
Observations	701	753	641	500
Sargan–Hansen	18.963	7.558	8.049	14.858
p–value	0.0001	0.0228	0.0179	0.0006
DWH test	4.490	13.736	9.806	0.152
p–value	0.0341	0.0002	0.0017	0.6963

Notes: Dependent variable is CI. Sargan–Hansen test has a null of valid instruments. Durbin–Wu–Hausman test has a null that instrumented variables are exogenous. t–statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.